ON THE EMANCIPATION OF PLS-SEM

Marko Sarstedt

Otto-von-Guericke-University Magdeburg

Chair of Marketing

Universitätsplatz 2

39106 Magdeburg, Germany

and

University of Newcastle, Faculty of Business and Law, Australia

E-mail: marko.sarstedt@ovgu.de

Christian M. Ringle (CORRESPONDING AUTHOR)

Hamburg University of Technology (TUHH)

Institute for Human Resource Management and Organizations (W-9)

Schwarzenbergstraße 95 (D)

21075 Hamburg, Germany

and

University of Newcastle, Faculty of Business and Law, Australia

E-mail: ringle@tuhh.de

Jörg Henseler

Radboud University Nijmegen

Institute for Management Research

P.O. Box 9108

6500 HK Nijmegen, The Netherlands

and

New University of Lisbon (Nova), Higher Institute for Statistics and Information Management (ISEGI), Portugal

E-mail: j.henseler@fm.ru.nl

Joseph F. Hair

Kennesaw State University

Burruss Building 423

Kennesaw 30144, GA, USA

E-mail: jhair3@kennesaw.edu

ON THE EMANCIPATION OF PLS-SEM:

A COMMENTARY ON RIGDON (2012)

INTRODUCTION

Partial least squares structural equation modeling (PLS-SEM) has become an increasingly visible methodological approach in business research. Several review studies document its increasing use across a variety of disciplines (Hair, Sarstedt, Pieper and Ringle 2012; Hair, Sarstedt, Ringle and Mena 2012; Ringle, Sarstedt and Straub 2012). In addition, *Long Range Planning*, one of the leading journals in the strategic management field, has devoted two special issues to the method (Hair, Ringle and Sarstedt 2012, 2013; Robins 2012). These articles in combination provide a clear indication of the importance of PLS-SEM for research and practice.

As with any development in research, the proponents and critics of PLS-SEM sometimes have heated debates on the method's advantages and disadvantages (e.g., Goodhue, Lewis and Thompson 2012; Marcoulides, Chin and Saunders 2012), disagreeing on whether it should be increasingly used or be applied at all. While an outright rejection of any method is certainly not good research practice and is unfounded in light of PLS-SEM's manifold advantageous features (e.g., Hair, Ringle and Sarstedt 2011; Henseler, Ringle and Sinkovics 2009), almost all methodological studies provide a balanced and constructive perspective on PLS-SEM's capabilities and limitations (e.g., Jöreskog and Wold 1982; Reinartz, Haenlein and Henseler 2009).

Nevertheless, much of the discussion has centered on a comparison of PLS-SEM with its longer established sibling: covariance-based structural equation modeling (CB-SEM). While these comparisons of statistical methods are important to learn more about situations that

favor the use of one method over the other, we believe that this research stream has reached a point that requires a different angle and new arguments to pursue.

Rigdon's (2012) thoughtful article takes the first important step in this respect by arguing that PLS-SEM should free itself from CB-SEM. It should renounce all mechanisms, frameworks, and jargon associated with factor models entirely. We fully agree with the spirit of this appeal but also acknowledge that this step is likely to trigger resistance from authors, reviewers, and editors because SEM is grounded in decades of psychometric research.

In this comment, we shed further light on two subject areas on which Rigdon (2012) touches in his discussion of CB-SEM and PLS-SEM.¹ Rigdon (2012) highlights ways to make better use of PLS-SEM's predictive capabilities, for example, by reverting to set correlations. While prediction is the mainstay of econometrics and all related methods, in a SEM context, it is often considered the ugly stepsister of testing causal relationships. We discuss this issue in more detail, highlighting the need to examine the predictive capabilities of models when developing and testing theories. In this context, we adopt Rigdon's (2012) notion that "researchers must develop an entirely different approach to measure validation." (Rigdon 2012, p. 354). By this means, we broach the issue of confirmatory versus exploratory modeling, the latter of which is – despite contrary notions – the dominant modeling approach in SEM. As a result of our discussion, we call for the continuous improvement of the PLS-SEM method to uncover its capabilities for theory testing while retaining its predictive character.

PREDICTION AND EXPLANATION

¹ Rigdon (2012) distinguishes between factor based and component-based SEM. In this comment, we refer to the statistical techniques that are mainly employed for these two different approaches to SEM. Hence, the term CB-SEM is used to refer to factor-based SEM, and PLS-SEM represents component-based SEM, because it is regarded as the "most fully developed and general system" of component-based SEM techniques (McDonald 1996; p. 240).

Rigdon (2012) argues that PLS-SEM should fully emancipate itself from CB-SEM by stressing its prediction-orientation rather than aiming at testing model relationships in an explanatory sense (i.e., theory testing). However, is there really a dichotomy between predictive and explanatory modeling?

In strategic management and other social sciences disciplines, statistical methods are predominantly used for explanation (i.e., theory testing). The goal is to apply data in order to test hypotheses relating to relationships embedded in a nomological net. Based on statistical inference, conclusions are drawn about the tenability of the causal hypotheses, effect sizes, and the appropriateness of the entire model. In contrast, when the focus is on prediction, the goal is to predict the output values through the input values or new observations.

The concept of prediction originates from an econometric perspective and is defined as “the estimate of an outcome obtained by plugging specific values of the explanatory variables into an estimated model” (Wooldridge 2003; p. 842). In the context of SEM, Bagozzi and Yi (2012) argue that prediction relates to a situation where a theory leads to the forecast of some relevant outcome. Specifically, they note the following: “If a study tests a theory and exogenous and endogenous variables are linked significantly according to the theory, we might term the relationship *explanatory* (e.g., ξ explains η) and then decide whether or not, or to what degree, causality can be claimed. [...] Nevertheless, we prefer to use the term *prediction* when an existing theory leads to the forecast or discovery of a new phenomenon or outcome. This latter usage is consistent with some philosophy of science characterizations of what constitutes a (strong) theory. That is, a theory that explains what it is supposed to explain is given less acclaim than one that also leads to new discoveries or predictions.” (Bagozzi and Yi 2012, p. 23). This notion is also underlined by Colquitt and Zapata-Phelan’s (2007) taxonomy of theoretical contributions of empirical articles whose conceptualization captures the degree to which predictions are grounded in logical speculation or existing

theory. Similarly, Roberts and Pashler (2000; p. 359) state that “a prediction is a statement of what a theory does and does not.” Jointly, these statements underline that prediction is an integral part of theory assessment, suggesting that researchers should not blindly rely on the explanation of relationships among constructs, but also keep the predictive capabilities of their model in mind (Bacharach 1989).

Unfortunately, the actual use of the SEM methodology (and others) does not adequately reflect this notion as researchers routinely neglect the importance of prediction. For example, in their analysis of more than 1,000 articles published in the *MIS Quarterly* and *Information Systems Research* journals between 1990 and 2006, Shmueli and Koppius (2010) identified only 52 empirical papers that focus on prediction. Several decades ago, the very same concern had been raised by Herman Wold, the inventor of the PLS-SEM method. He felt that SEM research generally focused too heavily on estimation and description at the expense of prediction (Dijkstra 2010). However, the problem might even have deeper roots in that researchers are not fully aware of the distinction between prediction and explanation. As Shmueli (2010, pp. 1-2) points out: “The lack of a clear distinction within statistics has created a lack of understanding in many disciplines of the difference between building sound explanatory models versus creating powerful predictive models, as well as confusing explanatory power with predictive power. The implications of this omission and the lack of clear guidelines on how to model for explanatory versus predictive goals are considerable for both scientific research and practice and have also contributed to the gap between academia and practice.”

We believe that the frequent neglect of predictive modeling and/or the confounding of explanatory and predictive modeling in the social sciences disciplines are the sources of misunderstandings and misapplications of the SEM methods. CB-SEM has been designed for explanation, not prediction. In fact, the factor indeterminacy problem makes factor-based

methods such as CB-SEM hardly suitable for predictive modeling and prediction-oriented research (Rigdon 2012). In contrast, PLS-SEM's prediction orientation was recognized very early on as one of the method's major strengths (Jöreskog and Wold 1982). The extraction of latent variable scores, in conjunction with the method explaining a large percentage of the variance in the indicator variables, is useful for accurately predicting latent variable scores (Anderson and Gerbing 1988). PLS-SEM's superiority in terms of prediction has also been validated in a simulation study by Reinartz et al. (2009, p. 340). They conclude that "PLS is preferable to ML-based CBSEM when the research focus lies in identifying relationships (i.e., prediction and theory development) instead of confirming them."

Correspondingly, prediction orientation has become one of the most prominently cited reasons for preferring PLS-SEM over CB-SEM. This is evidenced in practically all reviews of PLS-SEM use across different disciplines (e.g., Hair, Sarstedt, Pieper and Ringle 2012; Hair, Sarstedt, Ringle and Mena 2012; Ringle, Sarstedt and Straub 2012). However, these reviews also reveal that rather than fully subscribing to predictive modeling, PLS-SEM researchers frequently frame their results as reporting in a confirmatory sense. Instead, researchers should broaden their focus and also consider prediction as an important analysis goal. It is, after all, in the very nature of business research (as an applied discipline) to examine levers with which to predict improvements in company performance well, and thereby to provide recommendations for decision-making (Diamantopoulos, Sarstedt, Fuchs, Kaiser and Wilczynski 2012). Correspondingly, instead of mimicking the CB-SEM methodology, PLS-SEM should truly serve predictive modeling purposes.

ASSESSMENT OF RESULTS

An important element of the predictive modeling process relates to the evaluation of results. In his article, Rigdon (2012, p. 353) concludes that "the PLS path modeling community

should work to complete and validate a purely composite-based approach to evaluating modeling results.” This call implies that the existing PLS-SEM evaluation criteria are incomplete, not purely composite-based, or both. But what should PLS-SEM-based evaluation criteria achieve? From our perspective, criteria should provide answers to the following two questions: (1) Is the model able to explain and/or predict the dependent variable(s)? (2) Does the model adequately explain the observed correlations between variables? The first question refers to the use of adequate evaluation criteria for PLS-SEM, while the second question addresses the issue of model specification.

PLS-SEM Evaluation Criteria

The PLS-SEM toolbox includes a broad range of evaluation criteria to assess the adequacy of the measurement and structural models as described in the extant literature (Chin 1998, 2010; Hair, Hult, Ringle and Sarstedt 2014; Hair, Ringle and Sarstedt 2013; Hair, Sarstedt, Ringle and Mena 2012). However, there is a scarcity of clear, prediction-focused criteria.

The coefficient of the determination of endogenous latent variables (R^2) is typically used as a criterion of predictive power (Hair, Sarstedt, Ringle and Mena 2012; Henseler, Fassott, Dijkstra and Wilson 2011; Sarstedt, Wilczynski and Melewar 2013). However, the R^2 only has informative value with regard to in-sample prediction. In contrast, as a measure of predictive relevance, Stone-Geisser’s Q^2 (Geisser 1974; Stone 1974) provides a gauge for out-of-sample prediction. In the structural model, a Q^2 value larger than zero for a particular reflective endogenous latent variable indicates the path model’s predictive relevance for this particular construct. In contrast, a Q^2 value smaller than zero indicates that the model does not perform better than the simple average of the endogenous variable would do. It should, however, be noted that while comparing the Q^2 value to zero is indicative of whether an endogenous latent variable can be predicted, it does not say anything about the quality of the

prediction. In analogy to the f^2 effect size, researchers can compute the q^2 effect size, which allows for evaluating the relative impact of one construct in terms of its predictive relevance (Chin 1998; Hair, Hult, Ringle and Sarstedt 2014).

Even though Herman Wold recognized the usefulness of Stone-Geisser's Q^2 early on by stating that it fits PLS-SEM "like hand in glove" (Wold 1982, p. 30), this criterion is seldom reported in PLS-SEM studies (Hair, Sarstedt, Pieper and Ringle 2012; Hair, Sarstedt, Ringle and Mena 2012; Ringle, Sarstedt and Straub 2012). Furthermore, if reported, it is usually to be found in a results table without any critical analysis and further interpretation. Hence, the PLS-SEM community needs to better understand the use of suitable predictive evaluation criteria.

Relying on such well-known measures is not sufficient. PLS-SEM's toolbox has been and must be further extended to improve the predictive capabilities of the model estimation. For example, recent improvements address the critical issue of unobserved heterogeneity, which threatens the validity of all SEM results (Becker, Rai, Ringle and Völckner 2013; Sarstedt 2008a, b) and should become a standard means of evaluating PLS-SEM results (Hair, Sarstedt, Ringle and Mena 2012). Newly developed PLS-SEM segmentation methods – such as finite mixture partial least squares (FIMIX-PLS; Hahn, Johnson, Herrmann and Huber 2002; Sarstedt, Becker, Ringle and Schwaiger 2011; Sarstedt and Ringle 2010), the prediction-oriented segmentation of PLS-SEM results (PLS-POS; Becker, Rai, Ringle and Völckner 2013), or genetic algorithm segmentation (PLS-GAS; Ringle, Sarstedt and Schlittgen 2013; Ringle, Sarstedt, Schlittgen and Taylor) – can assist researchers conducting this kind of analysis. Other directions for extending the toolbox include PLS-SEM's ability to extract multiple dimensions from a given path model and set of indicators (e.g., Kuppelwieser and Sarstedt 2013). This is also noted by Rigdon (2012, p. 354): "PLS path modeling typically forms just one composite for each set of indicators, constraining the relationship

between each set of predictors to be unidimensional. Cohen's (1982) set correlation accounts for the explanatory power of relationships between sets of predictors across multiple dimensions. Comparing a particular model with a set correlation analysis would show just how much predictive ability a researcher was 'leaving on the table' for the sake of specifying unidimensional relationships." A corresponding extension has already been introduced by Apel and Wold (1982). Their deflation technique estimates latent variables in two and more dimensions by using the residuals of the previous dimension as the PLS-SEM algorithm's new input to obtain the estimations of the next dimension.

To summarize, PLS-SEM must overcome several problems before its value can be fully understood. First, further criteria and evaluation techniques for PLS-SEM (e.g., the use of root mean squared covariances, Tucker-Lewis and Bentler-Bonett indices, deflation) need to be considered. Second, PLS-SEM research should make use of existing criteria and develop further PLS-SEM-specific evaluation criteria and complementary analysis techniques that stress the method's predictive character. We expect lively academic discussions and increased numbers of research publications on PLS-SEM improvements in line with establishing a predictive modeling process tailored to PLS-SEM.

Model Misspecification

We fully agree with Rigdon's (2012) call that PLS-SEM should play out its strengths as a distinctive prediction-oriented approach to SEM with its own set of suitable evaluation criteria. However, we also believe that this notion should not mean that methodological research can lean back and stop seeking for solutions to the limitations of the method, such as its inability to detect model misspecification.

Philosophy of science tells us that valid conclusions can only be drawn from a system if its separate assumptions are true. For SEM – whether factor-based or component-based – it is

therefore crucial to identify and eliminate model misspecification in structural equation models (Hu and Bentler 1998). Hence, in addition to recognizing the situations where PLS-SEM has unique advantages over CB-SEM by further developing a set of suitable prediction-oriented evaluation criteria, we should also focus on answering the question whether the path model adequately explains the observed correlations between variables in order to avoid model misspecification.

The current guidelines for model evaluation have limited value in detecting model misspecification. In particular, none of the evaluation criteria recommended in extant PLS-SEM tutorials (e.g., Hair, Hult, Ringle and Sarstedt 2014; Henseler, Ringle and Sarstedt 2012; Henseler, Ringle and Sinkovics 2009) are able to identify problems of underparameterization. This is due to PLS-SEM, which unlike CB-SEM, lacks a global scalar function that could be used as an indicator of whether or not a model fits the data. In fact, the term fit has different meanings in the context of CB-SEM and PLS-SEM. Whereas in CBSEM, fit refers to the distance between an observed covariance matrix and an implied covariance matrix, in PLS-SEM fit relates to the degree to which a correlation or covariance-based criterion is being maximized (Hanafi 2007; Tenenhaus and Tenenhaus 2011). Correspondingly, “goodness-of-fit” measures in PLS-SEM such as those introduced by Tenenhaus, Esposito Vinzi, Chatelin and Lauro (2005) (i.e., GoF and GoF_{rel}), can – by definition – not offer what their names promise. Henseler and Sarstedt (2013, p. 577) conclude: “Neither of these indices is able to separate valid models from invalid models. In fact, researchers would be misled if they chose the model yielding the highest GoF.”²

A starting point for developing model fit measures that are capable of detecting misspecification could lie in Lohmöller’s (1989) work. More than 20 years ago, he

² The same holds for the FIT, and the adjusted FIT indices (Hwang, Malhotra, Kim, Tomiuk and Hong 2010) of generalized structured component analysis (Henseler 2012).

suggested that three evaluation criteria should be used to examine the adequacy of PLS path models. Lohmöller stressed that the outer residual correlation matrix as well as the inner residual correlation matrix may indicate that the model cannot fully explain the relationships between indicators, or may indicate that the relations included in the structural model do not fully explain the interplay of the constructs. The standardized root mean square residual (SRMR), which represents the Euclidean distance between the empirical correlation matrix and the model-implied correlation matrix, is a third instrument with which to detect model underestimation (Hu and Bentler 1998; Jöreskog 1993). The SRMR was initially proposed for use in combination with CB-SEM (Jöreskog and Sörbom 1981) but has also been transferred to PLS-SEM (Lohmöller 1989).³ Unfortunately, the extant literature has not adapted any of these measures for model evaluation in PLS-SEM or developed guidelines for their use (e.g., developing thresholds).

While evaluation criteria can help detect model misspecification, they are not sufficient to avoid misspecification. Currently, most variance-based SEM techniques have methodological limitations that restrict analysts' flexibility to specify models. For instance, most variance-based SEM techniques assume recursive models, which means that researchers cannot model feedback loops or endogeneity. Consequently, researchers using variance-based SEM can hardly avoid misspecification if the true model is not recursive. Researchers should develop ways to overcome the necessity for recursive path models.

³ Note that the SRMR indices are not exactly the same for the two techniques. Different from SRMR in CB-SEM, in PLS-SEM, the discrepancies between the empirical correlations and the model-implied correlations are zero for pairs of indicators belonging to the same construct.

It's All About Model Fit – Really?

Following the route to model fit also has risks, as can be seen in most CB-SEM applications. When using CB-SEM, it is very common for initially hypothesized models to exhibit inadequate fit. In response to this, researchers should reject the model and re-consider the study (which usually requires gathering new data). Alternatively, they frequently re-specify the original theoretically developed model in an effort to improve fit indices beyond the suggested threshold levels. By doing so, researchers arrive at a well-fitting model, which they conclude theory supports. Unfortunately, the latter is a best-case scenario that almost never applies in reality. Rather, researchers engage in exploratory specification searches for model set-ups that yield satisfactory levels of model fit.

In this context, Diamantopoulos (1994, p. 123) stresses that “the nature of the analysis is no longer confirmatory (i.e., testing a pre-determined system of hypotheses as reflected in the original model specification) but becomes exploratory in nature.” As models resulting from such specification searches often capitalize on the idiosyncrasies of the sample data (e.g., Chou and Bentler 1990; Green, Thompson and Babyak 1998; MacCallum and Browne 1993), “the final models that are the product of such modifications often do not correspond particularly well to the correct population models.” (Tomarken and Waller 2003, p. 595). Correspondingly, simulation studies show that a CB-SEM specification search is of rather poor quality (Homburg and Dobratz 1992). Furthermore, owing to the identification problems and decreased levels of statistical power when the sample size is limited (Reinartz, Haenlein and Henseler 2009; Vilares and Coelho 2013) – a circumstance researchers face more often than not (Diamantopoulos, Sarstedt, Fuchs, Kaiser and Wilczynski 2012) – such specification searches also tend to favor less complex models. When theories are more elaborate and path models increase in complexity, this tendency may prove problematic regarding advancing our understanding of certain phenomena (especially when using covariance-based approaches to

SEM, which are clearly limited in terms of estimating complex path models). Overall, it seems reasonable to conclude that while CB-SEM is traditionally viewed as a confirmatory tool, the contrary is actually true in practice.⁴

In contrast, PLS-SEM has been designed for research situations that are “simultaneously data-rich and theory-primitive” (Wold 1985, p. 589). Wold envisioned a discovery-oriented process, “a dialogue between the investigator and the computer” (Wold 1985, p. 590). Rather than a priori committing to a specific model and framing the statistical analysis as a hypothesis test, Wold expected that researchers would estimate numerous models in the course of learning something about the data and about the phenomena. It is ironic that Wold’s vision currently applies to many allegedly confirmatory CB-SEM analyses rather than many exploratory PLS-SEM analyses.

Therefore, instead of fully following the model fit maximization paradigm of explanatory modeling, the goal of predictive modeling should be to establish theoretically grounded models that have high predictive power. In this sense, methodological research should aim at uniting the strengths of both methods so that we truly arrive at “Not CB-SEM versus PLS-SEM” but “CB-SEM and PLS-SEM” (Hair, Sarstedt, Ringle and Mena 2012; p. 415).

CONCLUSION

Bentler and Huang’s (2014) as well as Dijkstra’s (2014) comments in this issue of *Long Range Planning* introduce corrections of PLS-SEM estimates that provide a method to mimic CB-SEM results perfectly. If these approaches hold what they promise, PLS-SEM is capable of delivering a comparable result to CB-SEM – if not of the same precision – but keeps most of its advantageous features (e.g., use of complex models, modeling flexibility, relatively low

⁴ Researchers will have a hard time admitting the exploratory character of their CB-SEM use considering (1) the problems that emerge from ex post factor analyses (Cliff 1983) and (2) the academic bias in favor of findings presented in confirmatory terms (Greenwald, Pratkanis, Leippe and Baumgardner 1986).

demands regarding data distribution and sample size, convergence behavior of the algorithm, and stability of results). These advances not only prove most arguments of PLS-SEM critics wrong, but also allow for adopting techniques and evaluation criteria that have been developed and established for CB-SEM in the past decades.

Exploiting the explanatory abilities of PLS-SEM for theory testing and emancipating the method by further developing its predictive capabilities will allow researchers to address both analytical concerns (i.e., explanation and prediction) by using a single method. In line with these considerations, the corrected and further extended PLS-SEM methods may be used in a combined explanatory and predictive modeling process, thereby constituting the third generation of multivariate analysis for strategic management and other social sciences disciplines (on the second generation of multivariate analysis see Fornell 1982). SEM research and applications in general – as one of the most important multivariate analysis techniques of the social sciences disciplines – will benefit from these fundamental developments.

Despite these advancements, PLS-SEM should retain its predictive character rather than fully subscribing to explanatory modeling. For this purpose, a predictive modeling procedure specific to PLS-SEM should be established that highlights the specifics of predictive modeling in terms of model building and assessment (Shmueli 2010). Regarding the latter, researchers should make better use of established criteria and introduce new ones to assess the predictive capabilities of their models. Moreover, PLS-SEM should use its existing procedures properly to avoid model misspecification.

Lastly, from a more generic academic research perspective, the recent exchange on Rigdon's (2012) article shows the benefits of a constructive discussion when dealing with controversial topics such as the "To PLS or Not to PLS" debate. Any extreme position that (oftentimes systematically) neglects the beneficial features of the other technique, and may result in

prejudiced boycott calls, is not good research practice and does not help to truly advance our understanding of methods and any other research subject (Hair, Ringle and Sarstedt 2012).

REFERENCES

- Anderson, James C., and David W. Gerbing. 1988. "Structural Equation Modeling in Practice: A Review and Recommended Two-Step Approach." *Psychological Bulletin* 103 (3): 411-423.
- Apel, Heino, and Herman Wold. 1982. "Soft Modeling with Latent Variables in Two or More Dimensions: PLS Estimation and Testing for Predictive Relevance." In *Systems Under Indirect Observations: Part II*. Eds. K. G. Jöreskog and H. Wold. Amsterdam: North-Holland, 209-247.
- Bacharach, Samuel B. 1989. "Organizational Theories: Some. Criteria for Evaluation." *Academy of Management Review* 14 (4): 496-515.
- Bagozzi, R.P., and Y. Yi. 2012. "Specification, evaluation, and interpretation of structural equation models." *Journal of the Academy of Marketing Science* 40 (1): 8-34.
- Becker, Jan-Michael, Arun Rai, Christian M. Ringle, and Franziska Völckner. 2013. "Discovering Unobserved Heterogeneity in Structural Equation Models to Avert Validity Threats." *MIS Quarterly* 37 (3): 665-694.
- Bentler, Peter M., and Wenjing Huang. 2014. "On Components, Latent Variables, PLS and Simple Methods: Reactions to Ridgon's Rethinking of PLS." *Long Range Planning* forthcoming.
- Chin, Wynne W. 1998. "The Partial Least Squares Approach to Structural Equation Modeling." In *Modern Methods for Business Research*. Ed. G. A. Marcoulides. Mahwah: Erlbaum, 295-358.
- Chin, Wynne W. 2010. "How to Write Up and Report PLS Analyses." In *Handbook of Partial Least Squares: Concepts, Methods and Applications (Springer Handbooks of Computational Statistics Series, vol. II)*. Eds. V. Esposito Vinzi, W. W. Chin, J. Henseler and H. Wang. Heidelberg, Dordrecht, London, New York: Springer, 655-690.
- Chou, C.P., and P.M. Bentler. 1990. "Model modification in covariance structure modeling: A comparison among likelihood ratio, Lagrange multiplier, and Wald tests." *Multivariate Behavioral Research* 25 (1): 115-136.
- Cliff, N. 1983. "Some cautions concerning the application of causal modeling methods." *Multivariate Behavioral Research* 18 (1): 115-126.
- Cohen, Jacob. 1982. "Set Correlation as a General Multivariate Data-Analytic Method." *Multivariate Behavioral Research* 17 (3): 301-341.

Colquitt, Jason A., and Cindy P. Zapata-Phelan. 2007. "Trends in Theory Building and Theory Testing: A Five-Decade Study of the Academy of Management Journal." *Academy of Management Journal* 50 (6): 1281-1303.

Diamantopoulos, Adamantios. 1994. "Modelling with LISREL: A guide for the uninitiated." *Journal of Marketing Management* 10 (1-3): 105-136.

Diamantopoulos, Adamantios, Marko Sarstedt, Christoph Fuchs, Sebastian Kaiser, and Petra Wilczynski. 2012. "Guidelines for Choosing Between Multi-item and Single-item Scales for Construct Measurement: A Predictive Validity Perspective." *Journal of the Academy of Marketing Science* 40 (3): 434-449.

Dijkstra, Theo K. 2010. "Latent Variables and Indices: Herman Wold's Basic Design and Partial Least Squares." In *Handbook of Partial Least Squares: Concepts, Methods and Applications* (Springer Handbooks of Computational Statistics Series, vol. II). Eds. V. Esposito Vinzi, W. W. Chin, J. Henseler and H. Wang. Heidelberg, Dordrecht, London, New York: Springer, 23-46.

Dijkstra, Theo K. 2014. "PLS' Janus Face." *Long Range Planning* forthcoming.

Fornell, Claes G. 1982. "A Second Generation of Multivariate Analysis: An Overview." In *A Second Generation of Multivariate Analysis*. Ed. C. Fornell. New York: Praeger, 1-21.

Geisser, Seymour. 1974. "A Predictive Approach to the Random Effects Model." *Biometrika* 61 (1): 101-107.

Goodhue, Dale L., William Lewis, and Ron Thompson. 2012. "Comparing PLS to Regression and LISREL: A Response to Marcolides, Chin, and Saunders." *MIS Quarterly*: accepted, online available.

Green, S.B., M.S. Thompson, and M.A. Babyak. 1998. "A Monte Carlo investigation of methods for controlling Type I errors with specification searches in structural equation modeling." *Multivariate Behavioral Research* 33 (3): 365-383.

Greenwald, Anthony G., Anthony R. Pratkanis, Michael R. Leippe, and Michael H. Baumgardner. 1986. "Under What Conditions Does Theory Obstruct Research Progress?" *Psychological Review* 93 (2): 216-229.

Hahn, Carsten, Michael D. Johnson, Andreas Herrmann, and Frank Huber. 2002. "Capturing Customer Heterogeneity Using a Finite Mixture PLS Approach." *Schmalenbach Business Review* 54 (3): 243-269.

Hair, Joe F., Marko Sarstedt, Christian M. Ringle, and Jeannette A. Mena. 2012. "An Assessment of the Use of Partial Least Squares Structural Equation Modeling in Marketing Research." *Journal of the Academy of Marketing Science* 40 (3): 414-433.

Hair, Joseph F., G. Tomas M. Hult, Christian M. Ringle, and Marko Sarstedt. 2014. *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Thousand Oaks: Sage.

Hair, Joseph F., Christian M. Ringle, and Marko Sarstedt. 2011. "PLS-SEM: Indeed a Silver Bullet." *Journal of Marketing Theory and Practice* 19 (2): 139-151.

Hair, Joseph F., Christian M. Ringle, and Marko Sarstedt. 2012. "Partial Least Squares: The Better Approach to Structural Equation Modeling?" *Long Range Planning* 45 (5-6): 312-319.

Hair, Joseph F., Christian M. Ringle, and Marko Sarstedt. 2013. "Partial Least Squares Structural Equation Modeling: Rigorous Applications, Better Results and Higher Acceptance." *Long Range Planning* 46 (1-2): 1-12.

Hair, Joseph F., Marko Sarstedt, Torsten M. Pieper, and Christian M. Ringle. 2012. "The Use of Partial Least Squares Structural Equation Modeling in Strategic Management Research: A Review of Past Practices and Recommendations for Future Applications." *Long Range Planning* 45 (5-6): 320-340.

Hanafi, Mohamed 2007. "PLS Path Modelling: Computation of Latent Variables with the Estimation Mode B." *Computational Statistics* 22 (2): 275-292.

Henseler, Jörg, Georg Fassott, Theo K Dijkstra, and Bradley Wilson. 2011. "Analysing quadratic effects of formative constructs by means of variance-based structural equation modelling" *European Journal of Information Systems* 21 (1): 99-112.

Henseler, Jörg. 2012. "Why Generalized Structured Component Analysis Is Not Universally Preferable to Structural Equation Modeling." *Journal of the Academy of Marketing Science* 40 (3): 402-413.

Henseler, Jörg, Christian M. Ringle, and Marko Sarstedt. 2012. "Using Partial Least Squares Path Modeling in International Advertising Research: Basic Concepts and Recent Issues." In *Handbook of Research in International Advertising*. Ed. S. Okazaki. Cheltenham: Edward Elgar Publishing, 252-276.

Henseler, Jörg, Christian M. Ringle, and Rudolf R. Sinkovics. 2009. "The Use of Partial Least Squares Path Modeling in International Marketing." In *Advances in International Marketing*. Eds. R. R. Sinkovics and P. N. Ghauri. Bingley: Emerald 277-320.

Henseler, Jörg, and Marko Sarstedt. 2013. "Goodness-of-Fit Indices for Partial Least Squares Path Modeling." *Computational Statistics* 28: 565-580.

Homburg, Ch, and Andreas Dobratz. 1992. "Covariance structure analysis via specification searches." *Statistical Papers* 33 (1): 119-142.

Hu, Li-tze, and Peter M. Bentler. 1998. "Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification." *Psychological Methods* 3 (4): 424-453.

Hwang, Heungsun, Naresh K. Malhotra, Youngchan Kim, Marc A. Tomiuk, and Sungjin Hong. 2010. "A Comparative Study on Parameter Recovery of Three Approaches to Structural Equation Modeling." *Journal of Marketing Research* 47 (4): 699-712.

Jöreskog, Karl G. 1993. "Testing Structural Equation Models." In *Testing Structural Equation Models*. Eds. K. A. Bollen and J. S. Long. Newbury Park: Sage, 294-316.

Jöreskog, Karl G., and Dag Sörbom. 1981. *LISREL V: Analyses of Linear Structural Relationships by Maximum Likelihood*. Chicago: National Educational Resources.

Jöreskog, Karl G., and Herman Wold. 1982. "The ML and PLS Techniques For Modeling with Latent Variables: Historical and Comparative Aspects." In *Systems Under Indirect Observation, Part I*. Eds. H. Wold and K. G. Jöreskog. Amsterdam: North-Holland, 263-270.

Kuppelwieser, Volker, and Marko Sarstedt. 2013. "Confusion About the Dimensionality and Measurement Specification of the Future Time Perspective Scale." *International Journal of Advertising* forthcoming.

Lohmöller, Jan-Bernd. 1989. *Latent Variable Path Modeling with Partial Least Squares*. Heidelberg: Physica.

MacCallum, Robert C., and Michael W. Browne. 1993. "The Use of Causal Indicators in Covariance Structure Models: Some Practical Issues." *Psychological Bulletin* 114 (3): 533-541.

Marcoulides, George A., Wynne W. Chin, and Carol Saunders. 2012. "When Imprecise Statistical Statements Become Problematic: A Response to Goodhue, Lewis, and Thompson." *MIS Quarterly* 36 (3): 717-728.

McDonald, Roderick P. 1996. "Path Analysis with Composite Variables." *Multivariate Behavioral Research* 31 (2): 239-270.

Reinartz, Werner J., Michael Haenlein, and Jörg Henseler. 2009. "An Empirical Comparison of the Efficacy of Covariance-Based and Variance-Based SEM." *International Journal of Research in Marketing* 26 (4): 332-344.

Rigdon, Edward E. 2012. "Rethinking Partial Least Squares Path Modeling: In Praise of Simple Methods." *Long Range Planning* 45 (5-6): 341-358.

Ringle, Christian M., Marko Sarstedt, and Rainer Schlittgen. 2013. "Genetic Algorithm Segmentation in Partial Least Squares Structural Equation Modeling." *OR Spectrum* DOI: 10.1007/s00291-013-0320-0.

Ringle, Christian M., Marko Sarstedt, Rainer Schlittgen, and Charles R. Taylor. "PLS path modeling and evolutionary segmentation." *Journal of Business Research* (0).

Ringle, Christian M., Marko Sarstedt, and Detmar W. Straub. 2012. "A Critical Look at the Use of PLS-SEM in MIS Quarterly." *MIS Quarterly* 36 (1): iii-xiv.

Roberts, S., and H. Pashler. 2000. "How persuasive is a good fit? A comment on theory testing." *Psychological Review* 107 (2): 358.

Robins, James A. 2012. "Partial-Least Squares." *Long Range Planning* 45 (5-6): 309-311.

Sarstedt, Marko. 2008a. "Market Segmentation with Mixture Regression Models." *Journal of Targeting, Measurement and Analysis for Marketing*: forthcoming.

Sarstedt, Marko. 2008b. "A Review of Recent Approaches for Capturing Heterogeneity in Partial Least Squares Path Modelling." *Journal of Modelling in Management* 3 (2): 140-161.

Sarstedt, Marko, Jan-Michael Becker, Christian M. Ringle, and Manfred Schwaiger. 2011. "Uncovering and Treating Unobserved Heterogeneity with FIMIX-PLS: Which Model

Selection Criterion Provides an Appropriate Number of Segments?" *Schmalenbach Business Review* 63 (1): 34-62.

Sarstedt, Marko, and Christian M. Ringle. 2010. "Treating Unobserved Heterogeneity in PLS Path Modelling: A Comparison of FIMIX-PLS with Different Data Analysis Strategies." *Journal of Applied Statistics* 37 (8): 1299-1318.

Sarstedt, Marko, Petra Wilczynski, and T. C. Melewar. 2013. "Measuring Reputation in Global Markets - A Comparison of Reputation Measures' Convergent and Criterion Validities" *Journal of World Business* 48 (3): 329-339.

Shmueli, Galit. 2010. "To Explain or to Predict?" *Statistical Science* 25 (3): 289-310.

Shmueli, Galit, and Otto R. Koppius. 2010. "Predictive Analytics in Information Systems Research." *MIS Quarterly* 35 (3): 553-572.

Stone, Mervyn. 1974. "Cross-Validatory Choice and Assessment of Statistical Predictions." *Journal of the Royal Statistical Society* 36 (2): 111-147.

Tenenhaus, Arthur, and Michel Tenenhaus. 2011. "Regularized Generalized Canonical Correlation Analysis." *Psychometrika* 76 (2): 257-284.

Tenenhaus, Michel, Vincenzo Esposito Vinzi, Yves-Marie Chatelin, and Carlo Lauro. 2005. "PLS Path Modeling." *Computational Statistics & Data Analysis* 48 (1): 159-205.

Tomarken, A. J., and N. G. Waller. 2003. "Potential Problems with "Well Fitting" Models." *Journal of Abnormal Psychology* 112 (4): 578-598.

Vilares, Manuel J., and Pedro S. Coelho. 2013. "Likelihood and PLS Estimators for Structural Equation Modeling: An Assessment of Sample Size, Skewness and Model Misspecification Effects." In *Advances in Regression, Survival Analysis, Extreme Values, Markov Processes and Other Statistical Applications*. Eds. J. Lita da Silva, F. Caeiro, I. Natário and C. A. Braumann. Berlin-Heidelberg: Springer, 11-33.

Wold, Herman. 1985. "Partial Least Squares." In *Encyclopedia of Statistical Sciences*. Eds. S. Kotz and N. L. Johnson. New York: Wiley, 581-591.

Wooldridge, Jeffrey M. 2003. *Introductory Econometrics. A Modern Approach*. Mason, OH: Thomson South-Western.