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GUIDELINES FOR TREATING UNOBSERVED HETEROGENEITY IN TOURISM RESEARCH: A COMMENT ON MARQUES AND REIS (2015)

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ABSTRACT

Considering unobserved heterogeneity in tourism studies when using PLS-SEM remains vastly important. This commentary further clarifies several important aspects concerning FIMIX-PLS: (1) the determination of the number of segments, (2) the specification of segments through explanatory variables, (3) the comparison of path coefficients across segments using multigroup analysis, and (4) the requirements for doing so.

KEYWORDS

Heterogeneity, partial least squares, structural equation modeling, PLS-SEM, latent class analysis, FIMIX-PLS

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1. INTRODUCTION

Accounting for heterogeneity in tourism studies remains important to avoid parameter misspecifications in empirical models (e.g., Mazanec, 2000; Mazanec, Ring, Stangl, & Teichmann, 2010). Approaches applied in tourism research that allow the examination of observed heterogeneity (e.g., Dolničar, 2004) include, for example, multi-group comparisons based on a priori information when employing regressions analysis (e.g., Ye, Zhang, & Yuen, 2013), partial least squares structural equation modeling (PLS-SEM) (e.g., Song, van der Veen, Li, & Chen, 2012), or covariance structural equation modeling (CB-SEM) (e.g., Jurowski & Gursoy, 2004). Differently, those approaches employed in tourism research to assess the potential of unobserved heterogeneity when certain grouping variables are not known a priori, for example, seek to identify latent classes (e.g., Mazanec, 2000; Mazanec, 2001). For instance, Assaf, Oh, and Tsionas (2015) employ Bayesian finite mixture modeling within CB-SEM, and Marques and Reis (2015) finite mixture modeling within PLS-SEM. It is the latter approach that this commentary focuses on.

In a recent contribution to this journal, Marques and Reis (2015) stress the importance of considering unobserved heterogeneity when analyzing path models using PLS-SEM. Indeed, if researchers fail to detect unobserved heterogeneity in PLS-SEM, the ensuing results may produce misleading conclusions (Becker, Rai, Ringle, & Völckner, 2013; Jedidi, Jagpal, & DeSarbo, 1997). In line with prior research on this topic (e.g., Hair, Ringle, & Sarstedt, 2011; Hair, Ringle,

& Sarstedt, 2013; Hair, Sarstedt, Ringle, & Mena, 2012; Rigdon, Ringle, & Sarstedt, 2010), we commend the authors for their endeavor to reinforce this important topic in tourism research, which has gained increasing prominence in the field. In light of the obvious benefits of examining unobserved heterogeneity in tourism research so to avoid parameter misspecifications when employing PLS-SEM (do Valle & Assaker, 2015), tourism researchers have started applying finite mixture PLS-SEM (FIMIX-PLS; Ferrari, Mondéjar-Jiménez, & Vargas-Vargas, 2010; Marques & Reis, 2015; Marques, Reis, & Menezes, 2013; Vargas-Vargas, Mondéjar Jiménez, Meseguer Santamaría, & Alfaro Navarro, 2009). The application of FIMIX-PLS in such studies is, however, not always adequate. Hence, in this commentary, we further illuminate several aspects related to existing FIMIX-PLS applications in tourism that we believe are fundamental to uncover and treat unobserved heterogeneity in PLS-SEM fully and adequately. Consideration of these aspects avoids parameter misspecifications, thereby improving the validity of findings that advance the tourism discipline.

2. DETERMINING THE NUMBER OF SEGMENTS IN FIMIX-PLS

One of the greatest challenges in the application of FIMIX-PLS relates to the determination of the number of segments to retain from the data (Sarstedt, Becker, Ringle, & Schwaiger, 2011). A misspecification can result in under- or oversegmentation and thus produce a flawed understanding of the behaviors of tourists and ensuing managerial or policy decisions that are ineffective to influence such behaviors (Andrews & Currim, 2003). To avoid such misspecification, a range of segment retention criteria serve to compare different segmentation solutions in terms of their model fit. Sarstedt, Becker, et al. (2011) demonstrate that researchers should jointly consider AIC_3 (Bozdogan, 1994) and CAIC (Bozdogan, 1987) when specifying the number of segments in PLS-SEM; representing an important aspect that clarifies and extends prior FIMIX-PLS applications in tourism research.

Segment retention criteria are not a panacea for determining the most suitable number of segments in FIMIX-PLS. The relative differences of the segment retention criteria results are often marginal for different numbers of segments. In such situations, the criteria offer only limited means to differentiate between the segment solutions. More importantly, AIC_3 and CAIC do not give any indication of how well separated the segments are. For this reason, the complementary use of the entropy-based measures is appropriate, such as the entropy normed statistic (EN; Ramaswamy, DeSarbo, Reibstein, & Robinson, 1993).

The EN ranges between 0 and 1; higher values indicate that more observations exhibit high probabilities of segment membership and thus uniquely belong to a certain segment. Sarstedt, Becker, et al. (2011, p. 52) note that "this criterion is critical to assessing whether the analysis produces well separated clusters, which is important for deriving management implications from any analysis." In line with prior research on this topic (e.g., Ringle, Sarstedt, & Mooi, 2010; Sarstedt & Ringle, 2010), EN values of less than 0.50 indicate fuzzy segment memberships that prevent meaningful segmentation and limit the practical value of the solution.

Apart from the above points, the identified segments must meet certain standards, particularly in terms of their size. FIMIX-PLS relies on the EM algorithm, which always converges to the prespecified number of segments. While this characteristic is generally advantageous, it also entails two problems. First, the final solution depends on the (random) starting values of the EM algorithm (McLachlan, 1988; Wedel & Kamakura, 2000), which may converge in local optimum solutions. Therefore, it is important to run FIMIX-PLS analyses repeatedly (e.g., 10 times; Ringle, Sarstedt, and Mooi, 2010). Second, the EM algorithm can force observations into an extraneous segment, even though they truly fit into another segment. Such extraneous segments are usually very small, account for only a marginal portion of heterogeneity in the overall data set and are unlikely to translate into meaningful segmentation opportunities (Rigdon, et al., 2010). The latter likely occurred in Marques and Reis (2015), in which Segment 4 merely comprises 24 observations. While this segment-specific sample size meets the frequently cited (but more often criticized) 10 times rule of thumb (Hair, Hult, Ringle, & Sarstedt, 2014), such small sample sizes are unlikely to increase confidence in the results as they tap into the idiosyncrasies of the specific set of observations. Instead of interpreting the segment-specific path coefficients for Segment 4, Marques and Reis (2015) could have dropped this segment and focused on the analysis and interpretation of the three larger segments.

Finally, any such a purely data-driven partitioning approach should include practical considerations (e.g., Sarstedt, Schwaiger, & Ringle, 2009), as the data can often only provide rough guidance as to the number of segments to select. Heuristics, such as information criteria or entropy measures, are fallible, as they are sensible to data and model characteristics. For example, even low levels of collinearity in the structural model can have adverse consequences for the criteria's performance (Becker, Ringle, Sarstedt, and Völckner (2015). As researchers should ensure that the results are interpretable and meaningful, drawing on a priori knowledge can complement such data-driven approach.

3. EXPLANATION OF THE LATENT SEGMENT STRUCTURE

The segments produced by FIMIX-PLS are latent. Turning such a statistically derived insight into actionable understanding requires researchers to interpret the segments in terms of observable and practically meaningful variables. To do so, they can conduct an *ex post* analysis to identify one or more explanatory variable(s) that match the method's partition in the best possible way (Hahn, Johnson, Herrmann, & Huber, 2002; Ringle, et al., 2010; Sarstedt & Ringle, 2010).

Marques and Reis (2015, p. 174) comment on this issue by stating that "targeting the segments would be facilitated if they were also profiled with visitor background variables," calling for further research in this regard. However, a FIMIX-PLS-based ex post analysis goes far beyond a mere profiling of segments and is an integral part of any latent class analysis. In an ex post analysis, the researchers should partition the data using an explanatory variable or a combination of several explanatory variables, which yields a grouping of data that largely corresponds to the one produced by FIMIX-PLS. Otherwise, the results remain abstract, as the computation of segment-specific estimates in FIMIX-PLS is not based on a hard clustering of observations based on their highest probability of segment membership but on weighted least squares regressions using these probabilities as input (Hahn, et al., 2002).

Different procedures enable the identifying of suitable explanatory variables. Hahn, et al. (2002) employ a procedure that regresses the adjusted probabilities of segment membership on a set of explanatory variables to identify the variable with the strongest impact on the partition solution. Other applications of FIMIX-PLS rely on classification and regression trees (Ringle, et al., 2010; Sarstedt & Ringle, 2010), and logistic regressions (Money, Hillenbrand, Henseler, & Da Camara, 2012; Wilden & Gudergan, 2015), among others. Importantly, to successfully run an *ex post* analysis, researchers must be able to consider a range of observable characteristics that can serve as possible input. Therefore, assessing the explanatory role of possible variables so that FIMIX-PLS can be implemented more completely must already be considered in the research design stage when collecting descriptive variables that may matter.

4. MULTIGROUP ANALYSIS AND MEASUREMENT INVARIANCE

Following the estimation of segment-specific PLS path models for each of the revealed segments, the next step is to compare the estimations using a multigroup analysis. Multigroup analysis allows testing whether numerical differences between segment-specific path coefficients are significantly different. Standard approaches to multigroup analysis in PLS-SEM, such as the parametric approach, permutation approach and PLS-MGA (for details see Hair, et al., 2014), univocally consider the two-segment case. However, latent class analyses frequently involve comparing more than two segments with each other, which is also the case in the illustration presented by Marques and Reis (2015). In such a situation, standard (nonparametric) ANOVA-type analysis techniques are not applicable, because they use bootstrap samples as direct input for the computation of the test statistic. For example, the Kruskal-Wallis test used in Marques and Reis (2015) is a Chi^2-based test whose test statistic increases when more bootstrap samples are used as input. Increasing the number of bootstrap samples therefore automatically increases the test statistic. Furthermore, using the Kruskal-Wallis test on FIMIX-PLS results is not appropriate, as the test assumes independent samples. However, as indicated above, FIMIX-PLS estimates coefficients from weighted least squares regressions and takes all observations—albeit with differing weightings—into account. Therefore, the segments in FIMIX-PLS are not independent which violates corresponding test requirements.

In such situations, an omnibus test of group differences for analyzing relationships among more than two segments is suitable (Sarstedt, Henseler, and Ringle (2011). This test uses a hard clustering of observations based on the (maximum) probabilities of segment membership as input and applies a combination of bootstrapping and permutation to derive a probability value of the variance explained by the grouping variable. If this variance is significantly different from zero, at least one group-specific coefficient significantly differs from the others.

A primary concern in multigroup analyses is ensuring measurement invariance (Vandenberg & Lance, 2000). Measurement invariance suggests that group differences in model estimates do not result from the differences in meanings of the latent variables across groups. For example, variations in the structural relationships between latent variables could stem from different meanings concerning the phenomena being measured or differences in perceived scale of measurement, rather than the true differences in the structural relationships (e.g., Steenkamp & Baumgartner, 1998). When measurement invariance is not demonstrated, any conclusions about differences in segment-specific model estimates are questionable.

Several established methods allow assessing measurement invariance. However, these fit CB-SEM and cannot be readily transferred to PLS-SEM's composite models. The measurement invariance of the composite models (MICOM) procedure (Henseler, Ringle, and Sarstedt (2015), as an applicable procedure to compare path coefficients across groups in the course of a multigroup analysis in PLS-SEM, assesses first configural and then compositional invariance, which is equivalent to partial measurement invariance.

7. SUMMARY AND CONCLUSION

Marques and Reis (2015) make a valuable contribution to the tourism research discipline by stressing the importance of considering unobserved heterogeneity in PLS-SEM. Using latent class techniques, tourism researchers can assess whether or not their results are distorted by unobserved heterogeneity (e.g., Mazanec, 2000). FIMIX-PLS takes an important role in this regard as it offers a means to treat heterogeneity nonparametrically in an SEM context. As Mazanec, et al. (2010, p. 35) note, "this is often more appropriate given that the data typically collected in tourism studies fail to meet the distributional assumption of parametric analysis." Such an assessment should also occur when researchers test theoretically established group differences, such as gender-related effects as unobserved heterogeneity can also exist within a priori formed segments (Rigdon, Ringle, Sarstedt, & Gudergan, 2011). If the analysis suggests that the data structures are heterogeneous, researchers must address this issue by partitioning the data into (latent) segments and conducting complementary analyses to obtain meaningful results.

Performing such a latent class analysis is not trivial, as it requires several choices that, if not made correctly, yield incorrect findings, interpretations, and conclusions. For this reason, this commentary sheds further light on several of the aspects that Marques and Reis (2015) raise and discusses some additional aspects that are fundamental to an adequate understanding of how to uncover and treat unobserved heterogeneity in PLS-SEM. These include (1) the determination of the number of segments, (2) their specification through explanatory variables, (3) the comparison of path coefficients across segments using multigroup analysis, and (4) the requirements for doing so (i.e., the establishment of measurement invariance). For researchers in tourism and other disciplines, Hair, Sarstedt, Matthews, and Ringle (2016) as well as Matthews, Sarstedt, Hair, and Ringle (2016) offer detailed explications about FIMIX-PLS and its systematic application.

Future research should aim at comparing and combining FIMIX-PLS with alternative PLS-SEM segmentation approaches such as prediction-oriented segmentation (PLS-POS; Becker, et al., 2013), genetic algorithm segmentation (PLS-GAS; Ringle, Sarstedt, & Schlittgen, 2014; Ringle, Sarstedt, Schlittgen, & Taylor, 2013) and iterative reweighted regression segmentation (PLS-IRRS; Schlittgen, Ringle, Sarstedt, & Becker, 2015). While FIMIX-PLS offers particularly useful capabilities for uncovering unobserved heterogeneity and determining the number of segments, PLS-POS, PLS-GAS and PLS-IRRS have some advantages when generating the final groups of data.

7. REFERENCES

Andrews, R. L., & Currim, I. S. (2003). Retention of Latent Segments in Regression-based Marketing Models. *International Journal of Research in Marketing, 20*, 315-321.

Assaf, A. G., Oh, H., & Tsionas, M. G. (2015). Unobserved Heterogeneity in Hospitality and Tourism Research. *Journal of Travel Research, forthcoming*.

Becker, J.-M., Rai, A., Ringle, C. M., & Völckner, F. (2013). Discovering Unobserved Heterogeneity in Structural Equation Models to Avert Validity Threats. *MIS Quarterly, 37*, 665-694.

Becker, J.-M., Ringle, C. M., Sarstedt, M., & Völckner, F. (2015). How Collinearity Affects Mixture Regression Results. *Marketing Letters, in press*.

Bozdogan, H. (1987). Model Selection and Akaike's Information Criterion (AIC): The General Theory and its Analytical Extensions. *Psychometrika, 52*, 345-370.

Bozdogan, H. (1994). Mixture-Model Cluster Analysis Using model Selection Criteria in a New Information Measure of Complexity. In H. Bozdogan (Ed.), *Proceedings of the First US/Japan Conference on Frontiers of Statistical Modelling: An Information Approach* (Vol. 2, pp. 69-113): Kluwer Academix Publishers.

do Valle, P. O., & Assaker, G. (2015). Using Partial Least Squares Structural Equation Modeling in Tourism Research: A Review of Past Research and Recommendations for Future Applications. *Journal of Travel Research, forthcoming*.

Dolničar, S. (2004). Beyond “Commonsense Segmentation”: A Systematics of Segmentation Approaches in Tourism. *Journal of Travel Research, 42*, 244-250.

Ferrari, G., Mondéjar-Jiménez, J., & Vargas-Vargas, M. (2010). Environmental Sustainable Management of Small Rural Tourist Enterprises. *International Journal of Environmental Research, 4*, 407-414.

Hahn, C., Johnson, M. D., Herrmann, A., & Huber, F. (2002). Capturing Customer Heterogeneity Using a Finite Mixture PLS Approach. *Schmalenbach Business Review, 54*, 243-269.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2014). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Thousand Oaks, CA: Sage.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a Silver Bullet. *Journal of Marketing Theory and Practice, 19*, 139-151.

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

Hair, J. F., Sarstedt, M., Matthews, L., & Ringle, C. M. (2016). Identifying and Treating Unobserved Heterogeneity with FIMIX-PLS: Part I - Method. *European Business Review, 28*, forthcoming.

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An Assessment of the Use of Partial Least Squares Structural Equation Modeling in Marketing Research. *Journal of the Academy of Marketing Science, 40*, 414-433.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A New Criterion for Assessing Discriminant Validity in Variance-based Structural Equation Modeling. *Journal of the Academy of Marketing Science, 43*, 115-135.

Jedidi, K., Jagpal, H. S., & DeSarbo, W. S. (1997). Finite-Mixture Structural Equation Models for Response-Based Segmentation and Unobserved Heterogeneity. *Marketing Science, 16*, 39-59.

Jurowski, C., & Gursoy, D. (2004). Distance Effects on Residents' Attitudes Toward Tourism. *Annals of Tourism Research, 31*, 296-312.

Marques, C., & Reis, E. (2015). How to Deal with Heterogeneity Among Tourism Constructs? *Annals of Tourism Research, 52*, 172-174.

Marques, C., Reis, E., & Menezes, J. (2013). A Finite Mixture Approach to Uncover the Heterogeneity in the Relationship Between Visit Motivation and Activity Preferences. In P. E. Oliveira, M. da Graça Temido, C. Henriques & M. Vichi (Eds.), *Recent Developments in Modeling and Applications in Statistics* (pp. 21-29). Berlin-Heidelberg: Springer.

Matthews, L., Sarstedt, M., Hair, J. F., & Ringle, C. M. (2016). Identifying and Treating Unobserved Heterogeneity with FIMIX-PLS: Part II – A Case Study. *European Business Review, 28*, forthcoming.

Mazanec, J. A. (2000). Mastering Unobserved Heterogeneity in Tourist Behavior Research. *Tourism Analysis, 5*, 171-176.

Mazanec, J. A. (2001). Mastering Unobserved Heterogeneity in Tourist Behaviour Research. In J. A. Mazanec, G. I. Crouch, J. R. Brent Richie & A. G. Woodside (Eds.), *Consumer Psychology of Tourism, Hospitality and Leisure* (Vol. 2, pp. 253-271). Wallingford-NewYork: CAB International.

Mazanec, J. A., Ring, A., Stangl, B., & Teichmann, K. (2010). Usage Patterns of Advanced Analytical Methods in Tourism Research 1988-2008: A Six Journal Survey. *Information Technology & Tourism, 12*, 17-46.

McLachlan, G. J. (1988). On the Choice of Starting Values for the EM Algorithm in Fitting Mixture Models. *Journal of the Royal Statistical Society. Series D (The Statistician), 37*, 417-425.

Money, K. G., Hillenbrand, C., Henseler, J., & Da Camara, N. (2012). Exploring Unanticipated Consequences of Strategy Amongst Stakeholder Segments: The Case of a European Revenue Service. *Long Range Planning, 45*, 395-423.

Ramaswamy, V., DeSarbo, W. S., Reibstein, D. J., & Robinson, W. T. (1993). An Empirical Pooling Approach for Estimating Marketing Mix Elasticities with PIMS Data. *Marketing Science, 12*, 103-124.

Rigdon, E. E., Ringle, C. M., & Sarstedt, M. (2010). Structural Modeling of Heterogeneous Data with Partial Least Squares. In N. K. Malhotra (Ed.), *Review of Marketing Research* (Vol. 7, pp. 255-296). Armonk: Sharpe.

Rigdon, E. E., Ringle, C. M., Sarstedt, M., & Gudergan, S. P. (2011). Assessing Heterogeneity in Customer Satisfaction Studies: Across Industry Similarities and Within Industry Differences. *Advances in International Marketing, 22*, 169-194.

Ringle, C. M., Sarstedt, M., & Mooi, E. A. (2010). Response-Based Segmentation Using Finite Mixture Partial Least Squares: Theoretical Foundations and an Application to American Customer Satisfaction Index Data. *Annals of Information Systems, 8*, 19-49.

Ringle, C. M., Sarstedt, M., & Schlittgen, R. (2014). Genetic Algorithm Segmentation in Partial Least Squares Structural Equation Modeling. *OR Spectrum, 36*, 251-276.
Ringle, C. M., Sarstedt, M., Schlittgen, R., & Taylor, C. R. (2013). PLS Path Modeling and Evolutionary Segmentation. *Journal of Business Research, 66*, 1318-1324.
Sarstedt, M., Becker, J.-M., Ringle, C. M., & Schwaiger, M. (2011). Uncovering and Treating Unobserved Heterogeneity with FIMIX-PLS: Which Model Selection Criterion Provides an Appropriate Number of Segments? *Schmalenbach Business Review, 63*, 34-62.
Sarstedt, M., Henseler, J., & Ringle, C. M. (2011). Multi-Group Analysis in Partial Least Squares (PLS) Path Modeling: Alternative Methods and Empirical Results. In M. Sarstedt, M. Schwaiger & C. R. Taylor (Eds.), *Advances in International Marketing, Volume 22* (Vol. 22, pp. 195-218). Bingley: Emerald.
Sarstedt, M., & Ringle, C. M. (2010). Treating Unobserved Heterogeneity in PLS Path Modelling: A Comparison of FIMIX-PLS with Different Data Analysis Strategies. *Journal of Applied Statistics, 37*, 1299-1318.
Sarstedt, M., Schwaiger, M., & Ringle, C. M. (2009). Do We Fully Understand the Critical Success Factors of Customer Satisfaction with Industrial Goods? - Extending Festge and Schwaiger's Model to Account for Unobserved Heterogeneity. *Journal of Business Market Management, 3*, 185-206.
Schlittgen, R., Ringle, C. M., Sarstedt, M., & Becker, J.-M. (2015). Segmentation of PLS Path Models by Iterative Reweighted Regressions. In J. Henseler, C. M. Ringle, J. L. Roldán & G. Cepeda (Eds.), *2nd International Symposium on Partial Least Squares Path Modeling: The Conference for PLS Users*. Seville.
Song, H., van der Veen, R., Li, G., & Chen, J. L. (2012). The Hong Kong Tourist Satisfaction Index. *Annals of Tourism Research, 39*, 459-479.
Steenkamp, J.-B. E. M., & Baumgartner, H. (1998). Assessing Measurement Invariance in Cross-National Consumer Research. *Journal of Consumer Research, 25*, 78-107.
Vandenberg, R. J., & Lance, C. E. (2000). A Review and Synthesis of the Measurement Invariance Literature: Suggestions, Practices, and Recommendations for Organizational Research. *Organizational Research Methods, 3*, 4-70.
Vargas-Vargas, M., Mondéjar Jiménez, J., Meseguer Santamaría, M. L., & Alfaro Navarro, J. L. (2009). Measurement of Cultural Tourism Motivations in World Heritage Cities: An Analysis Using FIMIX-PLS Algorithm. *Statistica Applicata, 21*, 153-165.
Wedel, M., & Kamakura, W. A. (2000). *Market Segmentation: Conceptual and Methodological Foundations* (2nd ed.). Boston: Kluwer.
Wilden, R., & Gudergan, S. (2015). The impact of dynamic capabilities on operational marketing and technological capabilities: investigating the role of environmental turbulence. *Journal of the Academy of Marketing Science, 43*, 181-199.
Ye, B. H., Zhang, H. Q., & Yuen, P. P. (2013). Cultural Conflicts or Cultural Cushion? *Annals of Tourism Research, 43*, 321-349.