MIS Quarterly

RESEARCH ESSAY

DISCOVERING UNOBSERVED HETEROGENEITY IN STRUCTURAL EQUATION MODELS TO AVERT VALIDITY THREATS

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Appendix A

Meta-Analyses of Information Systems Studies

Table A1. Meta-Analyses of IS Studies: Inconsistent Results Across a Range of Phenomena

IS Phenomenon	Reference, Journal	Scope	Meta-Analysis Purpose	Moderators/Contingency Variables Examined	Nature of Inconsistent Findings *(emphasis added)*
Decision Support System (DSS) Implementation Success	Alavi and Joachimsthaler 1992, MISQ	144 findings from 33 studies	Investigating the relationship between user-related factors and DSS implementation success	*Authors suggest that moderators could explain the large variance in effect sizes across studies.*	"*Reviews of information systems implementation research…have revealed that collectively, implementation studies have yielded* ***conflicting and somewhat confusing findings***."
Group Support Systems (GSS)	Dennis et al. 2001, MISQ	61 articles	Developing a new model for interpreting GSS effects on firm performance.	• Fit between the Task and the GSS Structures • Appropriation Support Received	"*Many previous papers have lamented the fact that the findings of past GSS* ***research have been inconsistent***. *This paper develops a new model for interpreting GSS effects on performance…*"

Table A1. Meta-Analyses of IS Studies: Inconsistent Results Across a Range of Phenomena (Continued)

IS Phenomenon	Reference, Journal	Scope	Meta-Analysis Purpose	Moderators/Contingency Variables Examined	Nature of Inconsistent Findings *(emphasis added)*
IT Investment Payoff	Kohli and Deveraj 2003, ISR	66 studies	Examining structural variables that explain why some IT payoff studies observe a positive effect and some do not.	• Dependent Classification • Sample Size • Data Source • Type of IT Impact • Type of IT Assets • Industry	"*…some studies have shown* ***mixed results*** *in establishing a relationship between IT investment and firm performance.*"
IT Innovation Adoption	Lee and Xia 2006, I&M	54 correlations from 21 studies	Investigating the effects of organizational size on IT innovation adoption.	• Type of Innovation • Type of Organization • Stage of Adoption • Scope of Size • Industry Sector	"*…empirical results on the relationship between them have been* ***disturbingly mixed and inconsistent****.…explain and resolve these mixed results by… examining the effects of six moderators on the relationship.*"
IT Project Escalation	Wang and Keil 2007, IRMJ	12 articles with 20 separate experiments	Investigating the effect size of sunk cost on project escalation and determining whether there is a difference in effect sizes between IT and non-IT projects.	• IT vs. Non-IT Projects	"*…because of the strong magnitude and* ***heterogeneity of effect sizes*** *for the sunk cost effect, we need more primary studies that investigate potential moderators of sunk cost.*"
Turnover of IT Professionals	Joseph et al. 2007, MISQ	33 studies	Integrating the 43 antecedents of turnover intentions of IT professionals in a unified framework using meta-analytic structural equation modeling.	• Age • Gender Ratio of Sample • Operationalization of Turnover Intention • Operationalization of Antecedents	"*…our narrative review finds* ***several inconsistent*** *(e.g., organization tenure and role conflict)* ***and inconclusive*** *(e.g., age and gender) findings.*"
IS Implementation Success	Sharma and Yetton 2003, MISQ	22 studies	Proposing a contingent model in which task interdependence moderates the effect of management support on implementation success.	• Task Interdependence	"*A meta-analysis of the empirical literature provides strong support for the model and begins to explain the* ***wide variance in empirical findings****.*" "*The theory developed and findings reported above help to explain the* ***inconsistent findings*** *in the literature.*"
	Sabherwal et al. 2006, Mgmt.Science	612 findings from 121 studies	Explaining the interrelationships among four constructs representing the success of a specific information system and the relationships of these IS success constructs with four user-related constructs and two constructs representing the context.	*Authors suggest that possible moderators include voluntariness of IS adoption and user characteristics such as age and gender.*	"*Despite considerable empirical research, results on the relationships among constructs related to information system (IS) success, as well as the determinants of IS success,* ***are often inconsistent****.*"
	Sharma and Yetton 2007, MISQ	27 studies	Proposing a contingent model in which the effect of training on IS implementation success is a function of technical complexity and task interdependence.	• Technical Complexity • Task Interdependence	"*Research has investigated the main effect of training on information systems implementation success. However,* ***empirical support for this model is inconsistent****.*"

Table A1. Meta-Analyses of IS Studies: Inconsistent Results Across a Range of Phenomena (Continued)

IS Phenomenon	Reference, Journal	Scope	Meta-Analysis Purpose	Moderators/Contingency Variables Examined	Nature of Inconsistent Findings *(emphasis added)*
Technology Acceptance	King and He 2006, I&M	88 studies	Summarizing TAM research and investigating conditions under which TAM may have different effects.	• Type of Users • Type of Usage	"*...all TAM relationships are not borne out in all studies; there is **wide variation in the predicted effects** in various studies…*" "*Since there **are inconsistencies in TAM results**, a meta-analysis is more likely to appropriately integrate the positive and the negative.*"
	Schepers and Wetzels 2007, I&M	51 articles containing 63 studies	Analyzing the role of subjective norms and three inter-study moderating factors.	• Type of Respondents • Type of Technology • Culture	"*First, the subjective norm has had a **mixed and inconclusive role**….Some studies found considerable impacts of it on the dependent variables. However, others did not find significant effects.*"
	Wu and Lederer 2009, MISQ	71 studies	Investigating the impact of environment-based voluntariness on the relationships among the four primary TAM constructs (i.e., ease of use, perceived usefulness, behavioral intention, and usage).	• Environment-Based Voluntariness	"*The Q statistic for each of the five correlations exceeded its cutoff, and thus the analyses confirmed heterogeneity for each (p < 0.01). **That is, of all the correlations vary across studies more than would be produced by sampling error.***"

Appendix B

Prediction-Oriented Segmentation for PLS Path Modeling (PLS-POS)

Overview

As a distance-based segmentation method, the PLS prediction-oriented segmentation (PLS-POS) method builds on earlier work on distance-measure-based segmentation—that is, the PLS typological path modeling (PLS-TPM) approach (Squillacciotti 2005) and its enhancement, the response-based detection of respondent segments in PLS (REBUS-PLS) (Esposito Vinzi et al. 2008). To extend the distance-measure-based PLS segmentation methods (including overcoming the methodological limitation of PLS-TPM and REBUS-PLS being applicable only to PLS path models with reflective measures (Esposito Vinzi et al. 2008; Sarstedt 2008)), the PLS-POS algorithm introduces three novel features: (1) it uses an explicit PLS-specific *objective criterion* to form homogeneous groups, (2) it includes a new *distance measure* that is appropriate for PLS path model with both reflective and formative measures and is able to uncover unobserved heterogeneity in formative measures, and (3) it ensures continuous *improvement of the objective criterion* throughout the iterations of the algorithm (hill-climbing approach). Table B1 shows the key technical differences of the new PLS-POS method in comparison with the main distance-based methods (i.e., PLS-TPM and REBUS-PLS) and the popular finite-mixture method for PLS (i.e., FIMIX-PLS).

The following sections explain in greater detail PLS-POS' distinctive features. To begin with, we focus on the description of PLS-POS' *objective criterion*. An explanation of the *distance measure* employed and its extension to use it for formative measurement models follows. Finally, we provide details on the *algorithm* with its specific steps and procedures and how it ensures the continuous improvement of the objective criterion.

Objective Criterion of PLS-POS

The main segmentation objective in PLS is to form homogenous groups of observations that show increased endogenous variables' explained variance (R^2) and, thus, provide an improved prediction (compared to the overall sample), which is in accordance with Anderberg's (1973, p.

Table B1. Comparison of the Technical Differences of FIMIX-PLS, PLS-TPM, REBUS-PLS, and PLS-POS

	Finite-Mixture Segmentation Approach	**Distance-Based Clustering Approaches**		
Algorithm Feature	**FIMIX-PLS** (Hahn et al. 2002)	**PLS-TPM** (Squillacciotti 2005; Squillacciotti 2010)	**REBUS-PLS** (Esposito Vinzi et al. 2010; Esposito Vinzi et al. 2008)	**PLS-POS**
Distributional Assumptions	Yes	No	No	No
Pre-clustering	No pre-clustering; random split of observations	Hierarchical classification based on redundancy residuals of the overall model	Hierarchical classification based on communality and structural residuals of the overall model	No pre-clustering; random split of observations and assignment to closest segment according to the distance measure
Distance measure	Has no distance measure†	Based on redundancy residuals of a single reflective endogenous latent variable	Based on communality residuals of all latent variables and structural residuals of all endogenous latent variables	Based on structural residuals of all endogenous latent variables with an extension that also accounts for heterogeneity in formative measures
Accounts for sources of heterogeneity in reflective measures?	No	No	Yes	No
Accounts for sources of heterogeneity in formative measures?	No	No‡	No ‡	Yes
Accounts for sources of heterogeneity in the structural model?	Yes	Yes	Yes	Yes
Assignment of observations to segments in each iteration	Proportional assignment of **all** observations to all segments based on the conditional multivariate normal densities to optimize the likelihood function	Assigns **all** observations to the closest segment	Assigns **all** observations to the closest segment	Assigns **only one** observation to the closest segment and assures improvement of an objective criterion (*R^2* of all endogenous latent variables) before accepting the change
Stop criterion	Extremely small improvement in log likelihood below critical value (or maximum number of iterations)	Stability of the classes' composition (no reassignment of observations); or maximum number of iterations	Stability of the classes' composition (number of reassignments below a critical percentage value of observations); or maximum number of iterations	Infinitesimal improvement in objective criterion (or maximum number of iterations)

†FIMIX-PLS assumes that each endogenous latent variable is distributed as a finite mixture of conditional multivariate normal densities. It uses these densities to estimate probabilities of segment memberships for each observation (proportional assignment) to optimize the likelihood function (which implicitly maximizes the segment-specific explained variance as part of the likelihood function).

‡"As in PLS-TPM, … [REBUS-PLS] 'distance' has, so far, only been implemented on models with reflective blocks. Although this is not to be considered a strict limitation for many applications, it must be pointed out that REBUS-PLS requires all blocks to be reflective" (Esposito Vinzi et al. 2008, p. 444). This requirement for models with only reflective measures also holds for the REBUS-PLS implementation in the PLSPM package (Sánchez and Trinchera 2013) for the statistical software R (R Core Team 2013).

195) notion of "clustering for maximum prediction." Consequently, possible PLS-specific and, thus, prediction-oriented objective criteria include the following: (1) the sum of the manifest variables' redundancy residuals in the reflective measures, (2) the sum of endogenous latent variables' R^2 values in the structural model, and (3) the goodness-of-fit criterion (GoF; Tenenhaus et al. 2005)[1] for assessing both the structural model and the reflective measures.

Including the residual terms of the manifest variables would only be appropriate to assess the explained variance and, thus, the predictive performance in reflective measures. Because PLS path modeling allows for the use of reflective and formative measures, objective criteria that draw on the manifest variables' residual terms do not support the general applicability of PLS-POS in both measurement models (i.e., reflective and formative). Consequently, the redundancy and community residual in the reflective measures, which are also included in the PLS-GoF measure, are not a useful criterion for the purpose of the PLS segmentation method.

An appropriate PLS-specific objective criterion maximizes the sum of the endogenous latent variables' R^2 values. In accordance with the PLS algorithm's objective (Lohmöller 1989; Wold 1982), PLS-POS focuses on maximizing the predictivity of each group by minimizing the sum of the endogenous latent variables' squared residuals in the PLS path model. Thus, the sum of each group's sum of R^2 values represents the objective criterion, which is explicitly defined and calculated in the PLS-POS algorithm. Every reassignment of observations in PLS-POS ensures improvement of the objective criterion (hill climbing approach; see description of the algorithm below). This objective criterion is suitable for any PLS path model regardless of whether such models include reflective or formative measures.

Distance Measure

To reassign observations, PLS-POS builds on the idea of Squillacciotti (2005) and Esposito Vinzi et al. (2008) to use a distance measure. We propose a new distance measure that is applicable to both reflective and formative measures and accounts for heterogeneity in the structural and the formative measurement model. This observation-to-group distance measure identifies appropriate observations to form homogenous groups and thereby depicts suitable candidates to improve the objective criterion. Within a group, each observation's capability to predict the endogenous latent variables in the PLS path model determines its distance to that group: the shorter the distance of observation i to group g, the higher the predictivity of observation i in group g.

It is important to understand the conceptual difference between observation i's membership in its current group k ($k = g$; $k, g \varepsilon G$) and its distance to an alternative group g ($k \neq g$; $k, g \varepsilon G$). For every endogenous latent variable b ($b \varepsilon B$), the latent variable scores of its direct predecessors $Y_{a_b ik}^{exogenous}$ and the corresponding structural model path coefficients $p_{a_b g}$ allow for the group-specific prediction of the endogenous latent variable scores $\left(\hat{Y}_{big}\right)$ via linear combinations $\left(\hat{Y}_{big} = \sum_{a_b=1}^{A_b} Y_{a_b ik}^{exogenous} \times p_{a_b g}\right)$. To calculate $\hat{Y}_{big}$, we use the latent variable scores of an observation's current group k and draw on the alternative group g's PLS path coefficients $p_{a_b g}$. The difference between the predicted value $\hat{Y}_{big}$ and the current group's latent variable scores Y_{bik} from the PLS path model estimation is the residual of observation i in group g for the endogenous latent variable b (Equation 1):

$$e_{big}^2 = \left(\hat{Y}_{big} - Y_{bik}\right)^2 = \left(\sum_{a_b=1}^{A_b} Y_{a_b ok}^{exogenous} \times p_{a_b g} - Y_{bik}^{endogenous}\right)^2 \tag{1}$$

The result of e_{big}^2 is an observation's predictivity in its current group when $k = g$ ($k, g \varepsilon G$). Furthermore, using the path coefficients $p_{a_b g}$ of alternative group-specific PLS estimations for $k \neq g$ ($k, g \varepsilon G$) provides a heuristic outcome for observation i's predictivity in each of the G-1 other possible group assignments. This establishes the new prediction-oriented PLS-POS distance measure, as presented by Equation (2):

$$D_{kig} = \sum_{b=1}^{B} \sqrt{\frac{e_{big}^2}{\sum_{i=1}^{I_k} e_{big}^2}} \tag{2}$$

The residuals of each observation i are divided by the sum of the residuals of all observations in i's current group k (I_k; sample size in group k). This ratio's square root is the distance of an observation i to group g for an endogenous latent variable b ($b \varepsilon B$). The sum over all

[1]Against its naming, PLS-GoF does not represent a measure of fit for PLS path modeling; see Henseler and Sarstedt (2012) for a discussion.

endogenous variables B in the PLS path model provides the total distance measure D_{kig}. The smaller the sum of the endogenous latent variables' squared residual values, the higher the predictivity of observation i in group g of the underlying PLS path model.

The distinction between formative and reflective measures requires that one pays particular attention in PLS path modeling (e.g., Diamantopoulos et al. 2001; Gudergan et al. 2008; Jarvis et al. 2003). Formative measures require (1) taking into account the indicators' heterogeneity for each measurement model within each group and/or (2) uncovering the significant differences in weights between the groups. Therefore, calculating the group-specific residual term in models with formative measures requires an extension of the group-specific residual e_{big}^2 in the distance measure. The latent variable scores $Y_{a_b jik}$ are replaced by linear combinations of the manifest variable scores $x_{a_b jik}$ and the corresponding measurement model's formative weights $\pi_{a_b jg}$. Equation (3) shows the calculation of the residual term for formative measures in the PLS path model.

$$e_{big}^2 = \left(\sum_{a_b=1}^{A_b} \sum_{j}^{J} x_{a_b jik} \times \pi_{a_b jg} \times p_{a_b g} - Y_{bik}^{endogenous} \right)^2 \tag{3}$$

The formative latent variable scores become a group-wise reestimated prediction of the associated manifest variables j when the squared residual is determined.

Algorithm

The segmentation process starts by randomly partitioning the overall sample into the prespecified number of G equal groups (Figure B1, Step 1). Calculating all group-specific PLS path model estimates reveals each observation's distance to its own and all other G-1 groups. A partitioning approach that assigns each observation to the group to which it has the shortest distance improves the initial segmentation.

Subsequently, the PLS-POS algorithm computes the group-specific PLS path modeling results (Figure B1, Step 2), updates the objective function (Figure B1, Step 3), and computes the observations' distances to all groups (Figure B1, Step 4.1). PLS-POS uses the distance measure to reassign observations based on the maximum value of the difference between an observation's distance to its current group (i.e., the group to which the observation has been assigned) and its distance to an alternative group (Equation 4).

$$\text{difference } \Delta_{kig} = \text{distance to current group } k\ (D_{kik}) - \text{distance to alternative group } g\ (D_{kig}) \tag{4}$$

Positive differences indicate that an observation has a shorter distance to the alternative group and, thus, potentially fits better in that group in terms of predictivity. This computation is conducted for all observations (Figure B1, Step 4.1). Each observation's maximum positive difference becomes part of the list of candidates (Figure B1, Step 4.2). Negative values are not considered because reassigning these observations possibly decreases the objective criterion. Subsequently, the candidates are sorted in descending order in terms of their positive distance differences (Figure B1, Step 4.3).

After the STOP statement, PLS-POS provides the group-specific PLS path model estimates for the final segmentation solution (Figure B1, Step 7). The maximum number of iterations should be sufficiently high (e.g., twice the number of observations in the overall sample) to obtain a solution that is close to the global optimum. The maximum search depth equals the number of observations in the sorted list of candidate observations for reassignment and, thus, may not exceed the number of observations in the overall sample. In early explorative research stages, one may use a reduced search depth for performance reasons. However, to determine the final segmentation result, the search depth should equal the maximum number of observations to ensure that the segmentation solution that minimizes the PLS-POS objective criterion (i.e., the endogenous latent variables' R^2 values in the PLS path model) has been identified.

Finally, three important issues are worth noting. First, PLS-POS only reassigns observations that improve the objective criterion. As such, the algorithm ensures the continuous improvement of the objective criterion and potentially provides a solution that is at least close to the global optimum. Second, in each iteration step, the algorithm changes the assignment of only one observation and calculates the group-specific PLS estimates of all observations and their new distance measures. Thus, in contrast to the alternative distance-based PLS segmentation approaches suggested in the literature to date (e.g., Esposito Vinzi et al. 2008; Squillacciotti 2005), PLS-POS avoids moving a sizeable set (more or less) of similar candidates from one group to another without improving the objective criterion. Third, owing to the implementation of a hill-climbing approach, PLS-POS could face the problem of ending in local optima. Wedel and Kamakura (2000) recommend running hill-climbing algorithms several times to attain alternative starting partitions and, finally, to select the best segmentation solution. The same procedure should be applied in the application of PLS-POS.

```
Step 1:   Create an initial segmentation to start the algorithm
    Step 1.1:   Randomly split the overall sample into K equally sized groups
    Step 1.2:   Compute the group-specific PLS estimates for the path model
    Step 1.3:   Establish each observation's distance to each group
    Step 1.4:   Assign each observation to the closest group
DO LOOP
Step 2:   Compute the group-specific PLS estimates for the path model
Step 3:   Determine the result of the objective criterion
Step 4:   Create a list of candidate observations for reassignment
    Step 4.1:   Establish the K-1 differences between each observation's distance to its current group and an alternative
                group
    Step 4.2:   IF an observation has one or more positive differences of distances, then
                Add the maximum difference and the observation's corresponding alternative group assignment to a list of
                candidates
              ELSE: Do nothing
    Step 4.3:   IF the list is empty, then
                GO TO STOP
              ELSE: Sort the list of candidate observations in descending order in terms of their positive distance differences
Step 5:   Improve the segmentation result
    Step 5.1:   Select the first observation in the list of candidate observations for reassignment
    DO LOOP
    Step 5.2:   Reassign the observation
    Step 5.2:   Compute the group-specific PLS estimates for the path model
    Step 5.3:   Determine the result of the objective criterion
    Step 5.4:   IF the observation's reassignment improves the objective criterion, then
                Save the current assignment and GO TO Step 6
              ELSE: Undo changes and continue with Step 5.5
    Step 5.5:   IF the list contains a subsequent observation following the currently selected observation on the list of
                candidates AND the maximum search depth has not been reached, then
                Select the next observation
              ELSE: GO TO Step 6
    UNTIL the objective criterion is improved
Step 6:   IF the maximum number of iterations OR the maximum search depth has been reached, then
      GO TO STOP
    ELSE: GO TO Step 2
UNTIL STOP
Step 7:   Compute the group-specific PLS path model estimates and provide the final segmentation results
```

Figure B1. The PLS-POS Algorithm

Appendix C

Design of the Multicollinearity Factor for the Simulation Study

The design of the simulation study for the formative measurement model includes three levels of multicollinearity between the formative indicators in the model. To simulate different levels of multicollinearity, we revert to Mason and Perreault's (1991) seminal study on multicollinearity (see also Grewal et al. 2004). We vary two levels of correlation patterns among the predictor variables reflecting conditions typically encountered by researchers and practitioners. In addition, a situation in which the indicators are uncorrelated (orthogonal) serves as a baseline for comparison (i.e., a perfect formative measure) because this model is unaffected by multicollinearity.

Table C1 shows the two multicollinearity levels based on Mason and Perreault, including the trace of $(X'X)^{-1}$, det(X'X), and condition number, as well as each variable's variance inflation factor (VIF) associated with a given level of multicollinearity.

Table C1. Levels of Multicollinearity

		Level 1				Level 2			
		X_1	X_2	X_3	X_4	X_1	X_2	X_3	X_4
	X_1	1.00				1.00			
	X_2	.65	1.00			.80	1.00		
	X_3	.40	.40	1.00		.60	.60	1.00	
	X_4	.00	.00	.00	1.00	.00	.00	.00	1.00
VIF		1.80	1.80	1.24	1.00	2.96	2.96	1.67	1.00
Trace $(X'X)^{-1}$		5.85				8.59			
Det(X'X)		.47				.22			
Condition no.		2.38				3.42			

Note: VIF = variance inflation factor

Appendix D

Simulation on the Effects of Unobserved Heterogeneity

The objective of this simulation study is to evaluate the implications of unobserved heterogeneity for structural model parameter estimates in PLS path models. The results show that unobserved heterogeneity has a strong adverse effect on PLS estimation outcomes: (1) parameter estimates are biased, (2) nonsignificant path coefficients at the group level become significant at the overall sample level that combines groups, (3) sign differences in the parameter estimates between groups are manifested as nonsignificant results at the overall sample level, and (4) explained variance of the model (R^2 of the endogenous variables) decreases. These erroneous estimates can lead to both Type I and Type II errors and to invalid inferences.

The simulation study uses a path model with two exogenous variables having a direct effect on one endogenous variable (all variables measured with five reflective indicators). We generate data for the true path coefficients of two groups by considering three situations of unobserved heterogeneity:

- Situation 1, where the path coefficients between group 1 and group 2 differ but show the same sign. We consider scenarios where all parameter estimates are positive (situation 1a) and negative (situation 1b) and where the magnitude in parameter differences between groups is low (.1) and high (.5).
- Situation 2, where unobserved heterogeneity causes sign reversal in parameter estimates across the two groups (i.e., group 1 has a positive path coefficient, while group 2 has a negative one).
- Situation 3, where one group has a nonsignificant parameter estimate and the other group has a significant parameter estimate. We distinguish between two different levels of parameter differences represented by the effect size of the significant parameter, namely .2 and .7.

We generated 100 sets of data for each condition and estimated the group-specific path coefficients, the overall sample path coefficients, and the t-values of these coefficients by employing the bootstrapping procedure on 1,000 subsamples (Henseler et al. 2009).

Table D1 presents the results. The left side shows the group-specific mean estimates of the path coefficients and their average t-values.[2] The columns on the right side show the mean path coefficients of the overall sample and the interpretation of the results in terms of bias, Type I and II errors, and variance explained (R^2).

[2]For a significance level of $\alpha = 0.05$ the t-value has to exceed the threshold of 1.98 in these conditions.

The results show that in all situations, biases in the parameter estimates distort effect sizes and cause misinterpretation of the path coefficients, which is especially problematic for comparative hypotheses (e.g., path coefficient 1 > path coefficient 2). Type I and Type II errors are exacerbated in situations where the group-specific parameters show inconsistent signs (i.e., situation 2 where signs are reversed across groups) and when at least one of the groups involves nonsignificant parameters while the other group does not (i.e., situation 3). In contrast, when all parameters are significant and show the same sign (situation 1), our results suggest that it is not very likely that Type II errors occur. In this situation, the existence of Type II errors depends on the effect size and the degree to which the increased power of the combined sample size compensates for the increase in standard errors due to unobserved heterogeneity. For all parameter constellations in our simulation study, the increased sample size compensates for the increase in standard errors.

The R^2 decreases in almost all situations, implying an inferior model fit at the overall sample level. We find particularly strong decreases in R^2 in situations in which the group-specific effect sizes are high; in contrast, R^2 is almost unaffected in situations showing low group-specific effect sizes.

Table D1. Results of the Simulation Study

Group-Specific Parameter Estimates			Pooled Parameter Estimate				
	Group 1 (n = 200)	Group 2 (n = 200)	Parameter (n = 400)	Biased?	Type I Error	Type II Error	Lower R^2
1a.	**.7** *(t = 18.57)* **.2** *(t = 3.94)* $R^2 = .53$	**.2** *(t = 3.84)* **.7** *(t = 19.64)* $R^2 = .53$	**.45** *(t = 11.36)* **.45** *(t = 11.54)* $R^2 = .41$	Yes	–	No	Yes
	.3 *(t = 4.95)* **.2** *(t = 3.31)* $R^2 = .13$	**.2** *(t = 3.36)* **.3** *(t = 4.79)* $R^2 = .13$	**.25** *(t = 5.70)* **.25** *(t = 5.73)* $R^2 = .12$	Yes	–	No	(Yes)
1b.	**-.7** *(t = 18.95)* **-.2** *(t = 3.70)* $R^2 = .53$	**-.2** *(t = 4.01)* **-.7** *(t = 19.27)* $R^2 = .53$	**-.45** *(t = -11.19)* **-.45** *(t = -11.44)* $R^2 = .24$	Yes	–	No	Yes
	-.3 *(t = 5.03)* **-.2** *(t = 3.14)* $R^2 = .13$	**-.2** *(t = 3.25)* **-.3** *(t = 5.09)* $R^2 = .13$	**-.25** *(t = -5.61)* **-.25** *(t = -5.80)* $R^2 = .12$	Yes	–	No	(Yes)
2.	**.7** *(t = 19.43)* **.2** *(t = 3.99)* $R^2 = .53$	**-.7** *(t = 19.09)* **-.2** *(t = 3.78)* $R^2 = .53$	**.00** *(t = .01)* **.00** *(t = .00)* $R^2 = .00$	Yes	–	100% 100%	Yes
3.	**.7** *(t = 19.94)* **.0** *(t = .01)* $R^2 = .49$	**.0** *(t = .01)* **.7** *(t = 19.89)* $R^2 = .49$	**.35** *(t = 7.61)* **.35** *(t = 7.38)* $R^2 = .24$	Yes	100% 100%	No	Yes
	.2 *(t = 3.38)* **.0** *(t = .00)* $R^2 = .04$	**.0** *(t = .01)* **.2** *(t = 3.17)* $R^2 = .04$	**.10** *(t = 1.88)* **.10** *(t = 1.90)* $R^2 = .02$	Yes	20% 40%	80% 60%	(Yes)
4.	**.0** *(t = .00)* **.0** *(t = .01)* $R^2 = .00$	**.0** *(t = .01)* **.0** *(t = .00)* $R^2 = .00$	**.00** *(t = .00)* **.00** *(t = .00)* $R^2 = .00$	–	No	–	–

Appendix E

ANOVA Results—Model 1 (Reflective Measures)

Tables E1 to E4 present the ANOVA results for model 1 (reflective measures) explaining MAB by method (PLS-POS/FIMIX-PLS) and the six design factors. All significant and substantial effects (i.e., all effects that explain more than 2 percent of the total variance in MAB implying a partial η^2 of more than .02) are highlighted in grey.

We find that the R^2, structural model heterogeneity, data distribution, and the interaction of structural model heterogeneity and R^2 have a substantial and significant effect on the MAB of both methods. Furthermore, there is a significant and substantial difference in the parameter recovery (MAB) of the two methods (PLS-POS and FIMIX-PLS) and for the interaction effects between the method and structural model heterogeneity and between the method and R^2.

Table E1. Between-Subjects Effects (Part I)

Source of Variance in MAB	df	F	Sig.	Partial η^2
Intercept	1	14,658.62	.000	.568
SMH	3	1,121.71	.000	.232
R^2	3	1,948.85	.000	.344
Sample Size	2	70.77	.000	.013
Reliability	1	1.88	.170	.000
Data Distribution	1	497.52	.000	.043
RSS	1	22.62	.000	.002
SMH × R^2	9	178.96	.000	.126
SMH × Sample Size	6	9.64	.000	.005
SMH × Reliability	3	1.33	.262	.000
SMH × Data Distribution	3	21.15	.000	.006
SMH × RSS	3	25.17	.000	.007
R^2 × Sample Size	6	11.44	.000	.006
R^2 × Reliability	3	.75	.524	.000
R^2 × Data Distribution	3	14.72	.000	.004
R^2 × RSS	3	29.76	.000	.008
Sample Size × Reliability	2	.48	.620	.000
Sample Size × Data Distribution	2	14.17	.000	.003
Sample Size × RSS	2	63.92	.000	.011
Reliability × Data Distribution	1	4.04	.044	.000
Reliability × RSS	1	.11	.735	.000
Data Distribution × RSS	1	267.72	.000	.023
SMH × R^2 × Sample Size	18	1.75	.026	.003
SMH × R^2 × Reliability	9	1.27	.249	.001
SMH × R^2 × Data Distribution	9	6.00	.000	.005
SMH × R^2 × RSS	9	2.32	.013	.002
SMH × Sample Size × Reliability	6	1.39	.216	.001

Note: df = degrees of freedom; MAB = mean absolute bias; RSS = relative segment size; SMH = structural model heterogeneity; all significant and substantial effects (i.e., all effects that explain more than 2% of the total variance in MAB implying a partial η^2 of more than .02) are highlighted in grey.

Table E2. Between-Subjects Effects (Part II)				
Source of Variance in MAB	**df**	**F**	**Sig.**	**Partial η^2**
SMH × Sample Size × Data Distribution	6	5.22	.000	.003
SMH × Sample Size × RSS	6	9.23	.000	.005
SMH × Reliability × Data Distribution	3	2.19	.087	.001
SMH × Reliability × RSS	3	3.50	.015	.001
SMH × Data Distribution × RSS	3	2.30	.075	.001
R^2 × Sample Size × Reliability	6	1.88	.080	.001
R^2 × Sample Size × Data Distribution	6	1.83	.089	.001
R^2 × Sample Size × RSS	6	13.00	.000	.007
R^2 × Reliability × Data Distribution	3	1.85	.135	.000
R^2 × Reliability × RSS	3	.42	.740	.000
R^2 × Data Distribution × RSS	3	7.83	.000	.002
Sample Size × Reliability × Data Distribution	2	1.65	.191	.000
Sample Size × Reliability × RSS	2	2.19	.112	.000
Sample Size × Data Distribution × RSS	2	17.14	.000	.003
Reliability × Data Distribution × RSS	1	1.08	.299	.000
SMH × R^2 × Sample Size × Reliability	18	.53	.948	.001
SMH × R^2 × Sample Size × Data Distribution	18	1.68	.036	.003
SMH × R^2 × Sample Size × RSS	18	2.11	.004	.003
SMH × R^2 × Reliability × Data Distribution	9	.68	.725	.001
SMH × R^2 × Reliability × RSS	9	.80	.614	.001
SMH × R^2 × Data Distribution × RSS	9	1.52	.135	.001
SMH × Sample Size × Reliability × Data Distribution	6	.60	.730	.000
SMH × Sample Size × Reliability × RSS	6	.79	.577	.000
SMH × Sample Size × Data Distribution × RSS	6	2.41	.025	.001
SMH × Reliability × Data Distribution × RSS	3	2.06	.104	.001
R^2 × Sample Size × Reliability × Data Distribution	6	1.52	.168	.001
R^2 × Sample Size × Reliability × RSS	6	1.04	.399	.001
R^2 × Sample Size × Data Distribution × RSS	6	4.75	.000	.003
R^2 × Reliability × Data Distribution × RSS	3	.26	.851	.000
Sample Size × Reliability × Data Distribution × RSS	2	.53	.588	.000
SMH × R^2 × Sample Size × Reliability × Data Distribution	18	.70	.817	.001
SMH × R^2 × Sample Size × Reliability × RSS	18	.70	.811	.001
SMH × R^2 × Sample Size × Data Distribution × RSS	18	.99	.473	.002
SMH × R^2 × Reliability × Data Distribution × RSS	9	.50	.874	.000
SMH × Sample Size × Reliability × Data Distribution × RSS	6	1.71	.115	.001
R^2 × Sample Size × Reliability × Data Distribution × RSS	6	1.41	.206	.001
SMH × R^2 × Sample Size × Reliability × Data Distribution × RSS	18	.96	.502	.002
Error	11,136			

Note: df = degrees of freedom; MAB = mean absolute bias; RSS = relative segment size; SMH = structural model heterogeneity.

Table E3. Within-Subjects Effects (Part I)

Source of Variance in MAB	df	F	Sig.	Partial η^2
Method	1	952.31	.000	.079
Method × SMH	3	217.47	.000	.055
Method × R^2	3	137.14	.000	.036
Method × Sample Size	2	4.66	.009	.001
Method × Reliability	1	.00	.974	.000
Method × Data Distribution	1	87.97	.000	.008
Method × RSS	1	104.01	.000	.009
Method × SMH × R^2	9	12.84	.000	.010
Method × SMH × Sample Size	6	2.79	.010	.002
Method × SMH × Reliability	3	.26	.854	.000
Method × SMH × Data Distribution	3	37.26	.000	.010
Method × SMH × RSS	3	.88	.450	.000
Method × R^2 × Sample Size	6	1.84	.087	.001
Method × R^2 × Reliability	3	.02	.995	.000
Method × R^2 × Data Distribution	3	19.48	.000	.005
Method × R^2 × RSS	3	3.98	.008	.001
Method × Sample Size × Reliability	2	.27	.765	.000
Method × Sample Size × Data Distribution	2	17.60	.000	.003
Method × Sample Size × RSS	2	16.60	.000	.003
Method × Reliability × Data Distribution	1	.02	.876	.000
Method × Reliability × RSS	1	.149	.700	.000
Method × Data Distribution × RSS	1	14.37	.000	.001
Method × SMH × R^2 × Sample Size	18	.89	.589	.001
Method × SMH × R^2 × Reliability	9	1.33	.215	.001
Method × SMH × R^2 × Data Distribution	9	2.07	.029	.002
Method × SMH × R^2 × RSS	9	4.56	.000	.004
Method × SMH × Sample Size × Reliability	6	.73	.626	.000
Method × SMH × Sample Size × Data Distribution	6	3.94	.001	.002
Method × SMH × Sample Size × RSS	6	1.72	.112	.001
Method × SMH × Reliability × Data Distribution	3	.74	.527	.000
Method × SMH × Reliability × RSS	3	1.02	.381	.000
Method × SMH × Data Distribution × RSS	3	18.88	.000	.005
Method × R^2 × Sample Size × Reliability	6	.28	.945	.000
Method × R^2 × Sample Size × Data Distribution	6	2.09	.051	.001
Method × R^2 × Sample Size × RSS	6	3.57	.002	.002
Method × R^2 × Reliability × Data Distribution	3	.29	.835	.000
Method × R^2 × Reliability × RSS	3	1.28	.278	.000
Method × R^2 × Data Distribution × RSS	3	8.97	.000	.002
Method × Sample Size × Reliability × Data Distribution	2	.69	.501	.000
Method × Sample Size × Reliability × RSS	2	.13	.876	.000
Method × Sample Size × Data Distribution × RSS	2	8.98	.000	.002
Method × Reliability × Data Distribution × RSS	1	.00	.993	.000

Note: df = degrees of freedom; MAB = mean absolute bias; RSS = relative segment size; SMH = structural model heterogeneity; all significant and substantial effects (i.e., all effects that explain more than 2% of the total variance in MAB implying a partial η^2 of more than .02) are highlighted in grey.

Table E4. Within-Subjects Effect (Part II)				
Source of Variance in MAB	df	F	Sig.	Partial η^2
Method × SMH × R^2 × Sample Size × Reliability	18	.56	.930	.001
Method × SMH × R^2 × Sample Size × Data Distribution	18	1.95	.009	.003
Method × SMH × R^2 × Sample Size × RSS	18	1.47	.092	.002
Method × SMH × R^2 × Reliability × Data Distribution	9	.95	.484	.001
Method × SMH × R^2 × Reliability × RSS	9	1.07	.380	.001
Method × SMH × R^2 × Data Distribution × RSS	9	1.96	.040	.002
Method × SMH × Sample Size × Reliability × Data Distribution	6	.54	.775	.000
Method × SMH × Sample Size × Reliability × RSS	6	1.23	.286	.001
Method × SMH × Sample Size × Data Distribution × RSS	6	2.62	.015	.001
Method × SMH × Reliability × Data Distribution × RSS	3	.30	.828	.000
Method × R^2 × Sample Size × Reliability × Data Distribution	6	1.20	.305	.001
Method × R^2 × Sample Size × Reliability × RSS	6	.56	.766	.000
Method × R^2 × Sample Size × Data Distribution × RSS	6	2.59	.016	.001
Method × R^2 × Reliability × Data Distribution × RSS	3	.34	.798	.000
Method × Sample Size × Reliability × Data Distribution × RSS	2	.34	.711	.000
Method × SMH × R^2 × Sample Size × Reliability × Data Distribution	18	.49	.965	.001
Method × SMH × R^2 × Sample Size × Reliability × RSS	18	.44	.980	.001
Method × SMH × R^2 × Sample Size × Data Distribution × RSS	18	1.76	.024	.003
Method × SMH × R^2 × Reliability × Data Distribution × RSS	9	.47	.897	.000
Method × SMH × Sample Size × Reliability × Data Distribution × RSS	6	1.62	.138	.001
Method × R^2 × Sample Size × Reliability × Data Distribution × RSS	6	.32	.928	.000
Method × SMH × R^2 × Sample Size × Reliability × Data Distribution × RSS	18	.83	.667	.001
Error(Method)	11,136			

Note: df = degrees of freedom; MAB = mean absolute bias; RSS = relative segment size; SMH = structural model heterogeneity.

Appendix F

ANOVA Results—Model 2 (Formative Measures)

Tables F1 to F7 present the ANOVA results for model 2 (formative measures) explaining MAB by method (PLS-POS/FIMIX-PLS) and the seven design factors. All significant and substantial effects (i.e., all effects that explain more than 2 percent of the total variance in MAB implying a partial η^2 of more than .02) are highlighted in grey.

We find that the R^2, structural and measurement model heterogeneity, sample size, multicollinearity and data distribution, the interaction of structural and measurement model heterogeneity, and the interaction of sample size and relative segment size have a substantial and significant effect on the MAB of both methods. Furthermore, there is a significant and substantial difference in the parameter recovery (MAB) of the two methods (PLS-POS and FIMIX-PLS) and for the two-way interaction effects between method and R^2, multicollinearity, and structural and measurement model heterogeneity. Method even has a significant and substantial interaction effect with both structural and measurement model heterogeneity (three-way interaction).

Table F1. Between-Subjects Effects (Part I)

Source of Variance in MAB	df	F	Sig.	Partial η^2
Intercept	1	142,696.80	.00	.740
SMH	3	7,605.33	.00	.313
MMH	2	2,912.99	.00	.104
R^2	3	4,286.31	.00	.204
Sample Size	2	864.77	.00	.033
RSS	1	629.83	.00	.012
Data Distribution	1	1,465.75	.00	.028
Multicollinearity	2	848.18	.00	.033
SMH × MMH	6	298.09	.00	.034
SMH × R^2	9	44.28	.00	.008
MMH × R^2	6	5.82	.00	.006

Note: df = degrees of freedom; MAB = mean absolute bias; MMH = measurement model heterogeneity; RSS = relative segment size; SMH = structural model heterogeneity; all significant and substantial effects (i.e., all effects that explain more than 2% of the total variance in MAB implying a partial η^2 of more than .02) are highlighted in grey.

Table F2. Between-Subjects Effects (Part II)				
Source of Variance in MAB	**df**	**F**	**Sig.**	**Partial η^2**
SMH × Sample Size	6	31.10	.00	.004
MMH × Sample Size	4	15.06	.00	.001
R^2 × Sample Size	6	46.43	.00	.006
SMH × RSS	3	78.68	.00	.005
MMH × RSS	2	.69	.50	.000
R^2 × RSS	3	87.86	.00	.005
Sample Size × RSS	2	1,426.86	.00	.054
SMH × Data Distribution	3	12.04	.00	.001
MMH × Data Distribution	2	7.61	.00	.000
R^2 × Data Distribution	3	3.21	.02	.000
Sample Size × Data Distribution	2	28.39	.00	.001
RSS × Data Distribution	1	2.26	.13	.000
SMH × Multicollinearity	6	109.17	.00	.013
MMH × Multicollinearity	4	287.84	.00	.022
R^2 × Multicollinearity	6	5.39	.00	.001
Sample Size × Multicollinearity	4	28.36	.00	.002
RSS × Multicollinearity	2	15.71	.00	.001
Data Distribution × Multicollinearity	2	16.50	.00	.001
SMH × MMH × R^2	18	25.86	.00	.009
SMH × MMH × Sample Size	12	5.18	.00	.001
SMH × R^2 × Sample Size	18	.78	.73	.000
MMH × R^2 × Sample Size	12	.48	.93	.000
SMH × MMH × RSS	6	5.48	.00	.001
SMH × R^2 × RSS	9	.60	.80	.000
MMH × R^2 × RSS	6	2.66	.01	.000
SMH × Sample Size × RSS	6	42.87	.00	.005
MMH × Sample Size × RSS	4	6.23	.00	.000
R^2 × Sample Size × RSS	6	59.73	.00	.007
SMH × MMH × Data Distribution	6	3.35	.00	.000
SMH × R^2 × Data Distribution	9	12.58	.00	.002
MMH × R^2 × Data Distribution	6	1.79	.10	.000
SMH × Sample Size × Data Distribution	6	9.02	.00	.001
MMH × Sample Size × Data Distribution	4	2.33	.05	.000
R^2 × Sample Size × Data Distribution	6	2.76	.01	.000
SMH × RSS × Data Distribution	3	13.81	.00	.001
MMH × RSS × Data Distribution	2	1.50	.22	.000
R^2 × RSS × Data Distribution	3	2.64	.05	.000
Sample Size × RSS × Data Distribution	2	21.48	.00	.001
SMH × MMH × Multicollinearity	12	18.31	.00	.004
SMH × R^2 × Multicollinearity	18	7.30	.00	.003
MMH × R^2 × Multicollinearity	12	1.16	.31	.000
SMH × Sample Size × Multicollinearity	12	11.15	.00	.003
MMH × Sample Size × Multicollinearity	8	3.17	.00	.001
R^2 × Sample Size × Multicollinearity	12	.88	.57	.000
SMH × RSS × Multicollinearity	6	12.44	.00	.001
MMH × RSS × Multicollinearity	4	8.08	.00	.001

Note: df = degrees of freedom; MAB = mean absolute bias; MMH = measurement model heterogeneity; RSS = relative segment size; SMH = structural model heterogeneity; all significant and substantial effects (i.e., all effects that explain more than 2% of the total variance in MAB implying a partial η^2 of more than .02) are highlighted in grey.

Table F3. Between-Subjects Effects (Part III)

Source of Variance in MAB	df	F	Sig.	Partial η^2
R^2 × RSS × Multicollinearity	6	1.29	.26	.000
Sample Size × RSS × Multicollinearity	4	18.22	.00	.001
SMH × Data Distribution × Multicollinearity	6	.94	.46	.000
MMH × Data Distribution × Multicollinearity	4	3.81	.00	.000
R^2 × Data Distribution × Multicollinearity	6	.88	.51	.000
Sample Size × Data Distribution × Multicollinearity	4	11.09	.00	.001
RSS × Data Distribution × Multicollinearity	2	12.97	.00	.001
SMH × MMH × R^2 × Sample Size	36	.75	.86	.001
SMH × MMH × R^2 × RSS	18	.86	.63	.000
SMH × MMH × Sample Size × RSS	12	5.31	.00	.001
SMH × R^2 × Sample Size × RSS	18	1.92	.01	.001
MMH × R^2 × Sample Size × RSS	12	.36	.98	.000
SMH × MMH × R^2 × Data Distribution	18	1.65	.04	.001
SMH × MMH × Sample Size × Data Distribution	12	3.87	.00	.001
SMH × R^2 × Sample Size × Data Distribution	18	1.36	.14	.000
MMH × R^2 × Sample Size × Data Distribution	12	.68	.78	.000
SMH × MMH × RSS × Data Distribution	6	1.80	.09	.000
SMH × R^2 × RSS × Data Distribution	9	1.57	.12	.000
MMH × R^2 × RSS × Data Distribution	6	.54	.78	.000
SMH × Sample Size × RSS × Data Distribution	6	8.98	.00	.001
MMH × Sample Size × RSS × Data Distribution	4	3.19	.01	.000
R^2 × Sample Size × RSS × Data Distribution	6	1.04	.40	.000
SMH × MMH × R^2 × Multicollinearity	36	2.16	.00	.002
SMH × MMH × Sample Size × Multicollinearity	24	.79	.75	.000
SMH × R^2 × Sample Size × Multicollinearity	36	1.62	.01	.001
MMH × R^2 × Sample Size × Multicollinearity	24	1.04	.41	.000
SMH × MMH × RSS × Multicollinearity	12	2.41	.00	.001
SMH × R^2 × RSS × Multicollinearity	18	1.19	.26	.000
MMH × R^2 × RSS × Multicollinearity	12	1.38	.17	.000
SMH × Sample Size × RSS × Multicollinearity	12	9.08	.00	.002
MMH × Sample Size × RSS × Multicollinearity	8	1.95	.05	.000
R^2 × Sample Size × RSS × Multicollinearity	12	1.38	.17	.000
SMH × MMH × Data Distribution × Multicollinearity	12	6.34	.00	.002

Note: df = degrees of freedom; MAB = mean absolute bias; MMH = measurement model heterogeneity; RSS = relative segment size; SMH = structural model heterogeneity.

Table F4. Between-Subjects Effects (Part IV)				
Source of Variance in MAB	**df**	**F**	**Sig.**	**Partial η^2**
SMH × R^2 × Data Distribution × Multicollinearity	18	1.72	.03	.001
MMH × R^2 × Data Distribution × Multicollinearity	12	1.12	.34	.000
SMH × Sample Size × Data Distribution × Multicollinearity	12	10.19	.00	.002
MMH × Sample Size × Data Distribution × Multicollinearity	8	.87	.54	.000
R^2 × Sample Size × Data Distribution × Multicollinearity	12	2.23	.01	.001
SMH × RSS × Data Distribution × Multicollinearity	6	9.02	.00	.001
MMH × RSS × Data Distribution × Multicollinearity	4	.49	.74	.000
R^2 × RSS × Data Distribution × Multicollinearity	6	1.10	.36	.000
Sample Size × RSS × Data Distribution × Multicollinearity	4	24.61	.00	.002
SMH × MMH × R^2 × Sample Size × RSS	36	.75	.86	.001
SMH × MMH × R^2 × Sample Size × Data Distribution	36	.74	.88	.001
SMH × MMH × R^2 × RSS × Data Distribution	18	1.20	.25	.000
SMH × MMH × Sample Size × RSS × Data Distribution	12	1.62	.08	.000
SMH × R^2 × Sample Size × RSS × Data Distribution	18	.69	.83	.000
MMH × R^2 × Sample Size × RSS × Data Distribution	12	1.20	.27	.000
SMH × MMH × R^2 × Sample Size × Multicollinearity	72	1.13	.21	.002
SMH × MMH × R^2 × RSS × Multicollinearity	36	1.66	.01	.001
SMH × MMH × Sample Size × RSS × Multicollinearity	24	1.66	.02	.001
SMH × R^2 × Sample Size × RSS × Multicollinearity	36	.52	.99	.000
MMH × R^2 × Sample Size × RSS × Multicollinearity	24	.75	.81	.000
SMH × MMH × R^2 × Data Distribution × Multicollinearity	36	.95	.55	.001
SMH × MMH × Sample Size × Data Distribution × Multicollinearity	24	1.52	.05	.001
SMH × R^2 × Sample Size × Data Distribution × Multicollinearity	36	1.33	.09	.001
MMH × R^2 × Sample Size × Data Distribution × Multicollinearity	24	.90	.60	.000
SMH × MMH × RSS × Data Distribution × Multicollinearity	12	1.52	.11	.000
SMH × R^2 × RSS × Data Distribution × Multicollinearity	18	1.90	.01	.001
MMH × R^2 × RSS × Data Distribution × Multicollinearity	12	1.45	.14	.000
SMH × Sample Size × RSS × Data Distribution × Multicollinearity	12	8.65	.00	.002
MMH × Sample Size × RSS × Data Distribution × Multicollinearity	8	1.13	.34	.000
R^2 × Sample Size × RSS × Data Distribution × Multicollinearity	12	.85	.60	.000
SMH × MMH × R^2 × Sample Size × RSS × Data Distribution	36	.98	.51	.001
SMH × MMH × R^2 × Sample Size × RSS × Multicollinearity	72	.84	.84	.001
SMH × MMH × R^2 × Sample Size × Data Distribution × Multicollinearity	72	1.07	.33	.002
SMH × MMH × R^2 × RSS × Data Distribution × Multicollinearity	36	1.24	.15	.001
SMH × MMH × Sample Size × RSS × Data Distribution × Multicollinearity	24	1.12	.32	.001
SMH × R^2 × Sample Size × RSS × Data Distribution × Multicollinearity	36	1.09	.32	.001
MMH × R^2 × Sample Size × RSS × Data Distribution × Multicollinearity	24	.87	.65	.000
SMH × MMH × R^2 × Sample Size × RSS × Data Distribution × Multicollinearity	72	1.05	.36	.002
Error	50,112			

Note: df = degrees of freedom; MAB = mean absolute bias; MMH = measurement model heterogeneity; RSS = relative segment size; SMH = structural model heterogeneity.

Table F5. Within-Subjects Effects (Part I)				
Source of Variance in MAB	**df**	**F**	**Sig.**	**Partial η^2**
Method	1	3,938.52	.00	.073
Method × SMH	3	3,987.98	.00	.193
Method × MMH	2	6,771.05	.00	.213
Method × R^2	3	826.32	.00	.047
Method × Sample Size	2	227.55	.00	.009
Method × RSS	1	171.66	.00	.003
Method × Data Distribution	1	2.97	.08	.000
Method × Multicollinearity	2	1,739.12	.00	.065
Method × SMH × MMH	6	976.49	.00	.105
Method × SMH × R^2	9	83.50	.00	.015
Method × MMH × R^2	6	6.13	.00	.001
Method × SMH × Sample Size	6	22.80	.00	.003
Method × MMH × Sample Size	4	3.13	.01	.000
Method × R^2 × Sample Size	6	3.95	.00	.000
Method × SMH × RSS	3	60.96	.00	.004
Method × MMH × RSS	2	12.78	.00	.001
Method × R^2 × RSS	3	15.69	.00	.001
Method × Sample Size × RSS	2	163.40	.00	.006
Method × SMH × Data Distribution	3	54.31	.00	.003
Method × MMH × Data Distribution	2	3.39	.03	.000
Method × R^2 × Data Distribution	3	5.19	.00	.000
Method × Sample Size × Data Distribution	2	12.45	.00	.000
Method × RSS × Data Distribution	1	56.16	.00	.001
Method × SMH × Multicollinearity	6	372.96	.00	.043
Method × MMH × Multicollinearity	4	257.24	.00	.020
Method × R^2 × Multicollinearity	6	9.69	.00	.001
Method × Sample Size × Multicollinearity	4	22.84	.00	.002
Method × RSS × Multicollinearity	2	5.85	.00	.000
Method × Data Distribution × Multicollinearity	2	11.81	.00	.000
Method × SMH × MMH × R^2	18	11.49	.00	.004
Method × SMH × MMH × Sample Size	12	2.44	.00	.001
Method × SMH × R^2 × Sample Size	18	3.68	.00	.001
Method × MMH × R^2 × Sample Size	12	1.39	.16	.000
Method × SMH × MMH × RSS	6	14.80	.00	.002
Method × SMH × R^2 × RSS	9	12.50	.00	.002
Method × MMH × R^2 × RSS	6	2.61	.02	.000
Method × SMH × Sample Size × RSS	6	47.94	.00	.006
Method × MMH × Sample Size × RSS	4	13.37	.00	.001
Method × R^2 × Sample Size × RSS	6	19.62	.00	.002
Method × SMH × MMH × Data Distribution	6	1.74	.11	.000
Method × SMH × R^2 × Data Distribution	9	5.01	.00	.001
Method × MMH × R^2 × Data Distribution	6	3.04	.01	.000
Method × SMH × Sample Size × Data Distribution	6	7.68	.00	.001
Method × MMH × Sample Size × Data Distribution	4	.30	.88	.000
Method × R^2 × Sample Size × Data Distribution	6	3.34	.00	.000
Method × SMH × RSS × Data Distribution	3	3.68	.01	.000
Method × MMH × RSS × Data Distribution	2	.76	.47	.000
Method × R^2 × RSS × Data Distribution	3	.43	.73	.000
Method × Sample Size × RSS × Data Distribution	2	19.04	.00	.001
Method × SMH × MMH × Multicollinearity	12	28.62	.00	.007
Method × SMH × R^2 × Multicollinearity	18	5.04	.00	.002
Method × MMH × R^2 × Multicollinearity	12	.46	.94	.000

Note: df = degrees of freedom; MAB = mean absolute bias; MMH = measurement model heterogeneity; RSS = relative segment size; SMH = structural model heterogeneity; all significant and substantial effects (i.e., all effects that explain more than 2% of the total variance in MAB implying a partial η^2 of more than .02) are highlighted in grey.

Table F6. Within-Subjects Effects (Part II)

Source of Variance in MAB	df	F	Sig.	Partial η^2
Method × SMH × Sample Size × Multicollinearity	12	11.91	.00	.003
Method × MMH × Sample Size × Multicollinearity	8	1.40	.19	.000
Method × R^2 × Sample Size × Multicollinearity	12	.91	.53	.000
Method × SMH × RSS × Multicollinearity	6	16.91	.00	.002
Method × MMH × RSS × Multicollinearity	4	3.91	.00	.000
Method × R^2 × RSS × Multicollinearity	6	1.19	.31	.000
Method × Sample Size × RSS × Multicollinearity	4	20.68	.00	.002
Method × SMH × Data Distribution × Multicollinearity	6	6.57	.00	.001
Method × MMH × Data Distribution × Multicollinearity	4	3.63	.01	.000
Method × R^2 × Data Distribution × Multicollinearity	6	.99	.43	.000
Method × Sample Size × Data Distribution × Multicollinearity	4	24.39	.00	.002
Method × RSS × Data Distribution × Multicollinearity	2	28.84	.00	.001
Method × SMH × MMH × R^2 × Sample Size	36	1.35	.08	.001
Method × SMH × MMH × R^2 × RSS	18	1.48	.08	.001
Method × SMH × MMH × Sample Size × RSS	12	1.99	.02	.000
Method × SMH × R^2 × Sample Size × RSS	18	2.48	.00	.001
Method × MMH × R^2 × Sample Size × RSS	12	2.34	.01	.001
Method × SMH × MMH × R^2 × Data Distribution	18	.86	.63	.000
Method × SMH × MMH × Sample Size × Data Distribution	12	2.68	.00	.001
Method × SMH × R^2 × Sample Size × Data Distribution	18	1.28	.19	.000
Method × MMH × R^2 × Sample Size × Data Distribution	12	.37	.97	.000
Method × SMH × MMH × RSS × Data Distribution	6	1.18	.32	.000
Method × SMH × R^2 × RSS × Data Distribution	9	3.45	.00	.001
Method × MMH × R^2 × RSS × Data Distribution	6	.51	.80	.000
Method × SMH × Sample Size × RSS × Data Distribution	6	8.37	.00	.001
Method × MMH × Sample Size × RSS × Data Distribution	4	1.21	.31	.000
Method × R^2 × Sample Size × RSS × Data Distribution	6	1.13	.34	.000
Method × SMH × MMH × R^2 × Multicollinearity	36	1.29	.11	.001
Method × SMH × MMH × Sample Size × Multicollinearity	24	1.28	.16	.001
Method × SMH × R^2 × Sample Size × Multicollinearity	36	1.36	.08	.001
Method × MMH × R^2 × Sample Size × Multicollinearity	24	1.05	.40	.001
Method × SMH × MMH × RSS × Multicollinearity	12	3.27	.00	.001
Method × SMH × R^2 × RSS × Multicollinearity	18	1.02	.43	.000
Method × MMH × R^2 × RSS × Multicollinearity	12	1.40	.16	.000
Method × SMH × Sample Size × RSS × Multicollinearity	12	8.14	.00	.002
Method × MMH × Sample Size × RSS × Multicollinearity	8	2.47	.01	.000
Method × R^2 × Sample Size × RSS × Multicollinearity	12	1.36	.18	.000
Method × SMH × MMH × Data Distribution × Multicollinearity	12	2.63	.00	.001
Method × SMH × R^2 × Data Distribution × Multicollinearity	18	1.65	.04	.001
Method × MMH × R^2 × Data Distribution × Multicollinearity	12	.82	.63	.000
Method × SMH × Sample Size × Data Distribution × Multicollinearity	12	7.24	.00	.002
Method × MMH × Sample Size × Data Distribution × Multicollinearity	8	1.01	.42	.000
Method × R^2 × Sample Size × Data Distribution × Multicollinearity	12	1.42	.15	.000
Method × SMH × RSS × Data Distribution × Multicollinearity	6	6.94	.00	.001
Method × MMH × RSS × Data Distribution × Multicollinearity	4	1.40	.23	.000
Method × R^2 × RSS × Data Distribution × Multicollinearity	6	1.59	.15	.000
Method × Sample Size × RSS × Data Distribution × Multicollinearity	4	15.65	.00	.001
Method × SMH × MMH × R^2 × Sample Size × RSS	36	1.88	.00	.001
Method × SMH × MMH × R^2 × Sample Size × Data Distribution	36	.80	.80	.001
Method × SMH × MMH × R^2 × RSS × Data Distribution	18	1.00	.45	.000

Note: df = degrees of freedom; MAB = mean absolute bias; MMH = measurement model heterogeneity; RSS = relative segment size; SMH = structural model heterogeneity.

Table F7. Within-Subjects Effects (Part III)				
Source of Variance in MAB	**df**	**F**	**Sig.**	**Partial η^2**
Method × SMH × MMH × Sample Size × RSS × Data Distribution	12	2.14	.01	.001
Method × SMH × R^2 × Sample Size × RSS × Data Distribution	18	1.53	.07	.001
Method × MMH × R^2 × Sample Size × RSS × Data Distribution	12	.77	.68	.000
Method × SMH × MMH × R^2 × Sample Size × Multicollinearity	72	.91	.70	.001
Method × SMH × MMH × R^2 × RSS × Multicollinearity	36	1.28	.12	.001
Method × SMH × MMH × Sample Size × RSS × Multicollinearity	24	1.95	.00	.001
Method × SMH × R^2 × Sample Size × RSS × Multicollinearity	36	1.37	.07	.001
Method × MMH × R^2 × Sample Size × RSS × Multicollinearity	24	.90	.60	.000
Method × SMH × MMH × R^2 × Data Distribution × Multicollinearity	36	.98	.50	.001
Method × SMH × MMH × Sample Size × Data Distribution × Multicollinearity	24	2.46	.00	.001
Method × SMH × R^2 × Sample Size × Data Distribution × Multicollinearity	36	1.49	.03	.001
Method × MMH × R^2 × Sample Size × Data Distribution × Multicollinearity	24	.70	.85	.000
Method × SMH × MMH × RSS × Data Distribution × Multicollinearity	12	1.75	.05	.000
Method × SMH × R^2 × RSS × Data Distribution × Multicollinearity	18	1.71	.03	.001
Method × MMH × R^2 × RSS × Data Distribution × Multicollinearity	12	1.37	.17	.000
Method × SMH × Sample Size × RSS × Data Distribution × Multicollinearity	12	8.67	.00	.002
Method × MMH × Sample Size × RSS × Data Distribution × Multicollinearity	8	1.29	.24	.000
Method × R^2 × Sample Size × RSS × Data Distribution × Multicollinearity	12	.78	.68	.000
Method × SMH × MMH × R^2 × Sample Size × RSS × Data Distribution	36	.85	.73	.001
Method × SMH × MMH × R^2 × Sample Size × RSS × Multicollinearity	72	1.05	.36	.002
Method × SMH × MMH × R^2 × Sample Size × Data Distribution × Multicollinearity	72	1.20	.11	.002
Method × SMH × MMH × R^2 × RSS × Data Distribution × Multicollinearity	36	1.53	.02	.001
Method × SMH × MMH × Sample Size × RSS × Data Distribution × Multicollinearity	24	2.53	.00	.001
Method × SMH × R^2 × Sample Size × RSS × Data Distribution × Multicollinearity	36	1.33	.09	.001
Method × MMH × R^2 × Sample Size × RSS × Data Distribution × Multicollinearity	24	1.25	.18	.001
Method × SMH × MMH × R^2 × Sample Size × RSS × Data Distribution × Multicollinearity	72	.96	.58	.001
Error(Method)	50,112			

Note: df = degrees of freedom; MAB = mean absolute bias; MMH = measurement model heterogeneity; RSS = relative segment size; SMH = structural model heterogeneity.

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