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# Bootstrapping and PLS-SEM: A step-by-step guide to get more out of your bootstrap results

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## ABSTRACT

Statistical inference, which relies on bootstrapping in partial least squares structural equation modeling (PLS-SEM), lies at the heart of developing practically relevant and academically rigorous theory. Inspection of PLS-SEM applications in European management research reveals that there is still much to be gained in terms of bootstrapping. This paper suggests several bootstrapping best practices and demonstrates how to conduct them for frequently encountered, yet often ignored, PLS-SEM situations such as the assessment of (non) direct effects, the comparison of effects, and the evaluation of the coefficient of determination.

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## 1. Introduction

The European management research field is on the verge of a revolution in terms of what is considered valuable scholarship (Chia, 2014; Hernes, 2014). More than ever before, there is a strong need and desire to return to European management scholarship's roots of being interdisciplinary, practically relevant, and academically and methodologically rigorous (Hernes, 2014; Kaplan, 2014; Kenworthy & Verbeke, 2015).

In this quest of what Chia (2014) refers to as a “scholarship of common sense,” partial least squares structural equation modeling (PLS-SEM) is a promising and relevant data analytical approach, as it is particularly suitable for providing empirical support for nascent theory; it is not impeded by a large number of stringent and impractical assumptions, and it is prediction-oriented in nature (Hair, Sarstedt, Pieper, & Ringle, 2012; Sarstedt, Ringle, Smith,

Reams, & Hair, 2014; Sosik, Kahai, & Piovoso, 2009).

The number of PLS-SEM applications in European management research is increasing and the benefits of PLS-SEM are well appreciated by many in the field thanks to some excellent overviews such as that of Hair et al. (2012). Nevertheless, the topic of statistical inference in PLS-SEM has received only limited attention so far, thereby failing to use PLS-SEM to its fullest potential in its contributions to the development of valuable European management theory.

In a statistical explanatory modeling context, statistical inference (i.e., hypothesis testing) occupies a pivotal place (cf. Cashen & Geiger, 2004; Thietart, 2001). In line with its distribution-free character, PLS-SEM relies on a bootstrap procedure to make statistical inferences. However, inspection of PLS-SEM applications in the European management literature reveals that only standard normal bootstrap confidence intervals are typically constructed to test whether relationships between adjacent constructs (i.e., direct relationships) are statistically significant. This is unfortunate, as bootstrapping has so much more to offer regarding the assessment of direct relationships

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and much more beyond this, such as testing the significance of both non-direct effects and the coefficient of determination as well as a formal comparison of effects.

The overall aim of this paper is to suggest (as well as empirically illustrate) some of the bootstrapping best practices applicable to commonly encountered European management research situations in a PLS-SEM context. Given this aim, the remainder of this paper is structured as follows. First, to identify key areas for improvement regarding the use of bootstrap procedures, the status quo of the bootstrap procedures used in PLS-SEM applications in European management research is described. Second, building on the previous step, an overview of the relevant literature related to key bootstrap decisions is presented. Inspection of this literature reveals that although much knowledge on bootstrapping exists, especially in more technical domains such as econometrics and psychometrics, it appears to be rather unknown to the European management research community. As such, the intent of this literature overview is therefore to provide clear and concise recommendations for improved bootstrap procedures in a PLS-SEM context relevant for European management researchers. Third, once again building on the observations regarding the PLS-SEM applications in European management research as well as the bootstrapping literature overview, a step-by-step guideline and a detailed empirical demonstration of how to practically perform the suggested bootstrap procedures in the PLS-SEM context are given. In particular, the focus will be on assessing the statistical significance of direct effects, non-direct effects, the coefficient of determination, and the comparison of effects. Finally, the paper concludes with a summary of several key recommendations for more optimal bootstrap procedures by European management researchers and a discussion of how the topics addressed in this paper relate to predictive analytics in PLS-SEM, and it touches upon this research's limitations.

## 2. Bootstrapping and PLS-SEM

This section starts with a brief introduction of the essence of bootstrapping and its merits. After that, an overview summarizing several bootstrap-related issues characterizing PLS-SEM applications in European management research is provided. This overview will then serve as a basis for suggesting several bootstrapping best practices in a PLS-SEM context.

### 2.1. Bootstrapping and its merits

In a nutshell, bootstrapping is a non-parametric resampling procedure that assesses the variability of a statistic by examining the variability of the sample data rather than using parametric assumptions to assess the precision of the estimates (for a detailed discussion of bootstrapping, see Efron and Tibshirani (1994)). In general,  $J$  samples are created in order to obtain  $J$  estimates for each parameter in the model. Typically, each of the  $J$  samples is obtained by sampling with replacement from the original data in such a way that every bootstrap sample contains as many cases as are present in the original data.

According to Mooney and Duval (1993) and Wood (2005), bootstrapping has several key advantages for applied researchers. First, the method is transparent and requires little knowledge of mathematics or probability theory. Second, the statistical assumptions on which the method depends are rather non-restrictive. This is particularly relevant for applied researchers since empirical data often do not meet restrictive assumption such as (multivariate) normality underlying many statistical models, which in turn influences the ability to make valid statistical

inferences from the data. Third, bootstrapping is widely applicable. As such, bootstrapping offers a solution to situations where conventional methods may be difficult or impossible to find. Related to this last point, it is important to explicitly note that you can almost bootstrap any number (in a PLS-SEM context).

The bootstrap procedures that take central stage in the current research are the so-called non-parametric bootstrap procedures (referred to by Efron (1982) as the original bootstrap). In addition, parametric bootstrap procedures exist (see, for instance, Davison & Hinkley, 2003). In contrast to non-parametric bootstrapping, which makes no assumptions about the underlying population distribution, parametric bootstrapping resamples a known distribution function (e.g., a normal distribution) whose parameters are estimated from the sample (Amiri, von Rosen, & Zwanzig, 2010).

The notion that parametric statistics are more powerful yet less robust than non-parametric statistics (Gibbons & Chakraborti, 2011; Siegel & Castellan, 1988) also holds for the distinction between parametric and non-parametric bootstrapping. Yet parametric bootstrapping is not often used in real-life statistical problems (Chernick, 1999). Following Davison and Hinkley (2003), this observation can be extended to PLS-SEM, as making assumptions about some parametric underlying distribution is not compatible with the distribution-free nature of PLS-SEM.

Although non-parametric bootstrapping does not rely on distributional assumptions, and thus produces more robust results, the bootstrap method will only provide a good approximation of the population parameter of interest if the sample is a good approximation of the population (Chernick, 1999). Put differently, bootstrapping needs good data and is not some miracle cure for dealing with bad data and/or (too) small samples. On the other hand, it should be noted that if the data were biased, parametric bootstrap procedures face the same problem and thus do not provide any remedy.

### 2.2. Bootstrapping and PLS-SEM applications

Departing from the work of Hair et al. (2012), Table 1 provides an overview of the bootstrap procedures reported for PLS-SEM applications in the field of European management published in key management journals.

Each of the PLS-SEM applications is described in terms of six criteria covering two general dimensions. The first dimension concerns the bootstrapping procedure employed in the PLS-SEM application. Here, attention is paid to the following criteria: (1) the type of bootstrap (or alternative resampling) procedure used; (2) the number of bootstrap samples; and (3) the statistic used to test the hypothesized (direct) effects. The second dimension describes the PLS-SEM applications in terms of the type of effects and/or parameters that could be formally assessed by means of a bootstrap procedure but are not necessarily performed by the researchers. Here distinctions are made among (1) direct effects (also covered under the previous dimension), (2) non-direct effects, (3) relative impact of effects, and (4) structural model performance in terms of the coefficient of determination of endogenous constructs. Regarding the non-direct effects as well as the relative effects, it should be noted that a possible reason these effects are not formally assessed in the PLS-SEM applications listed in Table 1 may be that these effects do not fit the scope of the particular study.

### 2.3. Observations on the applied bootstrap procedures

In terms of reporting, both surprising and shocking is the fact that 41.7% of the applications listed in Table 1 refrain from reporting

**Table 1**  
PLS-SEM applications in European management research.

	Applied bootstrap procedure		Effects/parameters tested by bootstrap procedure						
	Bootstrap?	# Bootstrap samples?	Direct effect	Non-direct effect	Comparison coefficients		Coefficient of determination ( $R^2$ )		
			Significance?	Present in model?	Significance?	Relevant in model?	Significance?	Reported?	Significance?
Bauer and Matzler (2014)	Not reported	Not reported	p-values "smaller than"	Yes	No	Yes	No	Yes	No
Becker, Klein and Wetzels (2012)	Yes	1000	p-values	Yes	Yes, p-values "smaller than"	Yes	No	Yes	No
Berghman, Matthyssens, Streukens, and Vandenbempt (2013)	Yes	5000	Percentile bootstrap CI	Yes	No	Yes	No	Yes	Yes, percentile bootstrap CI
Fink, Harms, and Kraus (2008)	Yes	500	t-values	Yes	No	Yes	No	Yes	No
Fornell, Lorange, and Roos (1990)	No, jackknife		t-values	Yes	No, but calculated	Yes	No	Yes	No
Gruber, Heineman, Brettel, and Hungeling (2010)	Not reported	Not reported	t-values	Yes	No	Yes	No	Yes	No
Jacob, Kleispass, and Pohl (2014)	Not reported	Not reported	t-values	Yes	No	Yes	No	Yes	No
Landau and Bock (2013)	Yes	500	Standard normal bootstrap CI	Yes	No	Yes	No	Yes	No
Macedo, Pinho, and Silva (2016)	Yes	5,000	t-values	Yes	Yes	Yes	No	Yes	No
Money, Hillenbrand, Henseler, and Da Camara (2012)	Yes	5,000	t-values	Yes	No	Yes	No	Yes	Yes, standard normal bootstrap CI
Nell and Ambos (2013)	Yes	1,000	Standard normal bootstrap CI	No		No		Yes	No
Swoboda, Meierer, Forscht, and Morschett (2011)	Not reported	Not reported	Standard normal bootstrap CI	Yes	No	Yes	No	Yes	No
Van Riel, Berens, and Dijkstra (2009)	Not reported	Not reported	p-value "smaller than"	Yes	No	Yes	No	Yes	No

Notes.  
PLS applications were selected using the search criteria suggested by Hair et al. (2012). Subsequently, only applications that were conducted in a European context were included.  
"Not reported" means that the researchers did not report this information in their publication.  
"p-values 'smaller than'" refers to situations in which no exact p-values are reported, but where the researchers indicate by means of asterisks whether the p-value associated with a parameter was smaller than the significance level (e.g.,  $p < 0.05$ ,  $p < 0.01$ ).  
To assess whether non-direct effects were present in the model, all research models were examined to see whether they contained indirect effects and whether the calculation of total effects would be feasible.  
The comparison of coefficients is deemed feasible for models that contained endogenous constructs that are a function of at least two different predictors.  
Publication details of the PLS-SEM applications can be found in the reference list, where they are indicated by means of an asterisk.

details regarding their bootstrap strategy. This is undesirable as it does not allow fellow researchers to judge the quality of the procedure on which the research findings are based.

In those cases where details regarding the employed bootstrap procedure are provided, three observations are noteworthy. First of all, symmetric bootstrap confidence intervals (or, equivalently, *t*-values based on the bootstrap distribution) are mostly used to evaluate model parameters (66.7%). Second, the number of bootstrap replications varies tremendously (minimum = 500; maximum = 5000). Third, although it concerns a relatively older application, some researchers opt for a jackknife procedure rather than bootstrapping. Related to these observations, the subsequent sections intend to provide several guidelines to more optimally conduct and report bootstrap procedures.

2.4. Evaluating statistical significance by means of bootstrapping

Based on the bootstrap output, various ways exist to assess the stability of the model parameters. According to Wood (2005), confidence intervals are preferred to *p*-values, as the former are less liable to misinterpretation and provide information about the size of the effect. Different possibilities exist when deciding to construct bootstrap confidence intervals. The three most common approaches (i.e., standard normal, percentile, and bias-corrected percentile bootstrap confidence intervals) that can be calculated

by hand using the original bootstrap output are listed in Table 2 together with their computational details.

The standard normal bootstrap confidence interval (as well as the closely related *t*-value) still relies on certain parametric distributional assumptions (i.e., *z*-distribution and *t*-distribution) and implies a bootstrap confidence interval that is symmetrically distributed around the mean. According to Efron and Tibshirani (1986), the standard normal bootstrap confidence interval works well with normal data. As previous studies (e.g., Hair, Ringle, & Sarstedt, 2013; Shook, Ketchen, Hult, & Kacmar, 2004) on methodological issues in management research have shown that the assumption of normal data often is unrealistic, standard normal bootstrap confidence intervals are likely to be suboptimal.

Unlike the standard normal bootstrap confidence interval, (bias-corrected) percentile bootstrap confidence intervals may be asymmetrically distributed around the mean parameter estimate. This is a valuable property, as the forced symmetry of the standard normal confidence intervals may have a negative influence on estimation accuracy, type I errors, and statistical power (Efron & Tibshirani, 1994). However, in small samples (especially with asymmetric distributions), the regular percentile bootstrap confidence interval does not work well (Chernick, 1999). In addition, a notable drawback of the regular percentile bootstrap confidence interval is the restrictive assumption that the bootstrapped sampling distribution is an unbiased estimate of the sample

**Table 2**  
The construction of bootstrap confidence intervals.

Standard normal bootstrap confidence interval	Percentile bootstrap confidence interval	Bias-corrected percentile bootstrap confidence interval
Conduct <i>J</i> bootstrap samples each with <i>n</i> cases (here <i>n</i> equals the size of the original sample) and save the <i>J</i> bootstrap estimates for parameter $\gamma$ . Determine the mean value of the <i>J</i> estimates of $\gamma$ (i.e., $\bar{\gamma}$ ) as well as the accompanying standard deviation (i.e., $SD_{\gamma}$ ). The lower bound (i.e., LB) and upper bound (i.e., UB) of the standard normal bootstrap confidence interval are given by equations (1a) and (1b), respectively. In equations (1a) and (1b), $z_{(1-\alpha/2)}$ is the $(1-\alpha/2)$ critical value of the standard normal distribution.	Determine the $(\alpha/2)^{th}$ and the $(1-\alpha/2)^{th}$ percentile of the bootstrap distribution consisting of <i>J</i> estimates for parameter $\gamma$ . The lower bound (LB) and upper bound (UB) of the percentile bootstrap confidence interval are given by equations (2a) and (2b), respectively.	Determine $Z'_{LB}$ and $Z'_{UB}$ , defining the percentiles for the bias-corrected bootstrap confidence interval using equations (3a) and (3b), respectively.  $Z'_{LB} = Z_0 + ((Z_0 + Z_{LB}) / (1 - \hat{\alpha}(Z_0 + Z_{LB})))$ (3a) $Z'_{UB} = Z_0 + ((Z_0 + Z_{UB}) / (1 - \hat{\alpha}(Z_0 + Z_{UB})))$ (3b)
$LB = \bar{\gamma} - (z_{(1-\alpha/2)} \cdot SD_{\gamma})$ (1a)	$LB = (\alpha/2) \cdot 100\%$ (2a)	In equations (3a) and (3b), $Z_{LB}$ and $Z_{UB}$ are the standard normal distribution's <i>z</i> -score associated with the confidence interval's lower and bound percentile, respectively, and $Z_0$ is the <i>z</i> -score corresponding to the percentage of the <i>J</i> bootstrap estimates that are smaller than the original sample estimate. Finally, the term $\hat{\alpha}$ is the so-called acceleration coefficient and is determined by equation (3c). $\hat{\alpha} = \frac{\sum_{i=1}^n (\bar{\theta} - \theta_i)^3}{6 \left[ \sum_{i=1}^n (\bar{\theta} - \theta_i)^2 \right]^{3/2}}$ (3c)
$UB = \bar{\gamma} + (z_{(1-\alpha/2)} \cdot SD_{\gamma})$ (1b)	$UB = (1 - \alpha/2) \cdot 100\%$ (2b)	In equation (3c), $\theta_i$ is the <i>i</i> <sup>th</sup> bootstrap estimate and $\bar{\theta}$ is the average value of the <i>J</i> bootstrap estimates.
		Determine the proportion of the normal distribution to the left of $Z'_{LB}$ and $Z'_{UB}$ , denoted by, respectively, $\pi_{LB}$ and $\pi_{UB}$ . The lower bound (i.e., LB) and upper bound (i.e., UB) of the bias-corrected percentile bootstrap confidence interval correspond to the observations of the sorted distribution of the <i>J</i> bootstrap estimates as implied by equations (3d) and (3e). $LB = (\pi_{LB} \cdot J)^{th} \text{ observation}$ (3d) $UB = (\pi_{UB} \cdot J)^{th} \text{ observation}$ (3e)

distribution (Mooney & Duval, 1993).

In response to the drawbacks mentioned above, Efron (1982) proposed the biased-corrected and accelerated percentile bootstrap confidence interval,<sup>1</sup> which adjusts for bias due to non-symmetric distribution and the shape (i.e., skewness) of the distribution. Several simulation studies, such as MacKinnon, Lockwood, and Williams (2004) and Williams and MacKinnon (2008), have been conducted to assess the relative performance of the three bootstrap confidence interval approaches discussed above and presented in Table 2. These studies show that (bias-corrected) percentile bootstrap confidence intervals are indeed superior to standard normal bootstrap confidence intervals in terms of power, accuracy, and type I error rate. The superiority of the bias-corrected percentile bootstrap confidence interval over the regular percentile bootstrap confidence interval is less straightforward. The bias-corrected percentile confidence interval possesses greater power, although the percentile bootstrap had better control of type I error (MacKinnon et al., 2004). Nevertheless, based on a simulation study involving complex structural models, Williams and MacKinnon (2008) concluded that the bias-corrected percentile bootstrap is the method of choice. Hence, it is recommended to construct bias-corrected percentile confidence intervals to make statistical inferences when using PLS-SEM.

### 2.5. Number of bootstrap samples

The large spread in the number of bootstrap samples used in the PLS-SEM applications listed in Table 1 is indicative of a lack of guidelines regarding the minimum number of bootstrap samples needed.

Regardless of the type of bootstrap confidence interval constructed, the ability to draw valid conclusions depends to a large extent on the number of bootstrap samples or repetitions ( $J$ ) used to construct the bootstrap confidence interval. The work of Andrews and Buchinsky (2000, 2001, 2002) revealed that the minimal number of bootstrap repetitions needed depends on the desired level of accuracy, the confidence level, the distribution of the data (kurtosis), and the type of bootstrap confidence interval constructed. For instance, their Monte Carlo simulation revealed that for a general accepted level of accuracy (i.e., 95%)  $J = 2522$  and  $J = 6962$  bootstrap repetitions are needed for, respectively, symmetric confidence intervals and bias-corrected intervals. Note that their figures represent minimum values as they are derived under the assumption of normality.

Taking into account that the construction of bias-corrected percentile bootstrap confidence intervals is considered the most optimal choice in assessing PLS-SEM parameters, it is therefore advised to use at least 10,000 bootstrap samples. This well exceeds previous suggestions made by Efron and Tibshirani (1994) and Preacher and Hayes (2008) to draw, respectively, 1000 or 5000 bootstrap samples. Given the speed of today's desktop computing technology, 10,000 bootstrap samples will hardly be problematic.

### 2.6. Other resampling strategies than bootstrapping

Although hardly used in PLS-SEM applications in European management research, the jackknife resampling approach occasionally appears in PLS-SEM analyses. Hence, for the sake of completeness, the jackknife procedure, as well as its inferiority compared with the bootstrap, is discussed below.

Similar to the bootstrap procedure, the jackknife also rests on the assumption that the empirical sample distribution is a good proxy for the population distribution. The resampling procedure underlying the jackknife, however, is different from the bootstrap. The jackknife estimator of a parameter is found by systematically omitting each observation from a dataset and calculating the estimate using the remaining  $N-1$  observations and then taking the average of all possible  $N$  jackknife estimates (see also Sahinler and Topuz (2007) for more computational details as well as a discussion of the  $N - d$  or "delete  $d$ " jackknife).

Thus, the jackknife can be considered a special case of bootstrapping. According to Efron (1982) and Efron and Tibshirani (1994), the bootstrap is preferred over the jackknife, as the latter only uses limited information about the statistic, thereby being less efficient. Furthermore, Sahinler and Topuz (2007) showed that the bootstrap outperforms the jackknife in a least-squares context. Finally, despite the arguments favoring the use of the bootstrap over the jackknife, researchers will probably not be confronted with the choice between these two resampling methods as software packages such as SmartPLS 3 (Ringle, Wende, & Becker, 2015) no longer offer the possibility to perform a jackknife procedure.

### 2.7. Reporting your bootstrap procedure

In line with the observation that often information concerning the performed bootstrap procedure is lacking, as well as the suggestions for improved bootstrap procedures outlined above, the following is proposed regarding the bootstrap procedure's reporting. As a minimum, in addition to the statistic under consideration, key elements that should always be reported regarding the bootstrap analysis include the number of bootstrap runs, the size of the bootstrap samples, the applied significance level, a detailed and justified description of the way hypotheses are tested, and the specification of the relevant software parameters (e.g., Ringle et al.'s (2015) SmartPLS3 with no sign change).

## 3. Bootstrapping and hypothesis testing

Having outlined the merits of bias-corrected percentile bootstrap confidence intervals and their construction, this section shows how these confidence intervals can be implemented to formally test hypotheses associated with frequently encountered research phenomena. The structure of this section is again guided by the data in Table 1. In particular, the focus is on the second dimension on which the applications are described. Furthermore, in order to promote the practical implementation of the ideas put forward in this paper, an empirical illustration using real-life data is provided.

### 3.1. Observations in PLS-SEM applications

Inspection of the PLS-SEM applications reported in Table 1 reveals that many of the possibilities that bootstrapping has to offer remain unexploited by researchers. In particular, the following observations deserve attention.

First of all, many PLS-SEM applications (92.3%) contain non-direct effects (i.e., indirect and total effects). Although PLS-SEM is perfectly capable of dealing with complex nomological networks containing a large number of constructs (Ringle, Sarstedt, & Straub, 2012), the resulting non-direct effects are hardly investigated in depth (see Becker et al. (2012) for a notable exception). Although relatively few of the PLS-SEM applications explicitly assessed the possible non-direct effects, inspection of recent studies (e.g., Jayasinghe, 2016; Rubera & Tellis, 2014; Wo, Ambrose, & Schminke, 2015) in key management journals shows that the non-direct

<sup>1</sup> The term bias-corrected bootstrap confidence interval in this paper refers to Efron's (1986) bias-corrected and accelerated percentile bootstrap confidence interval.



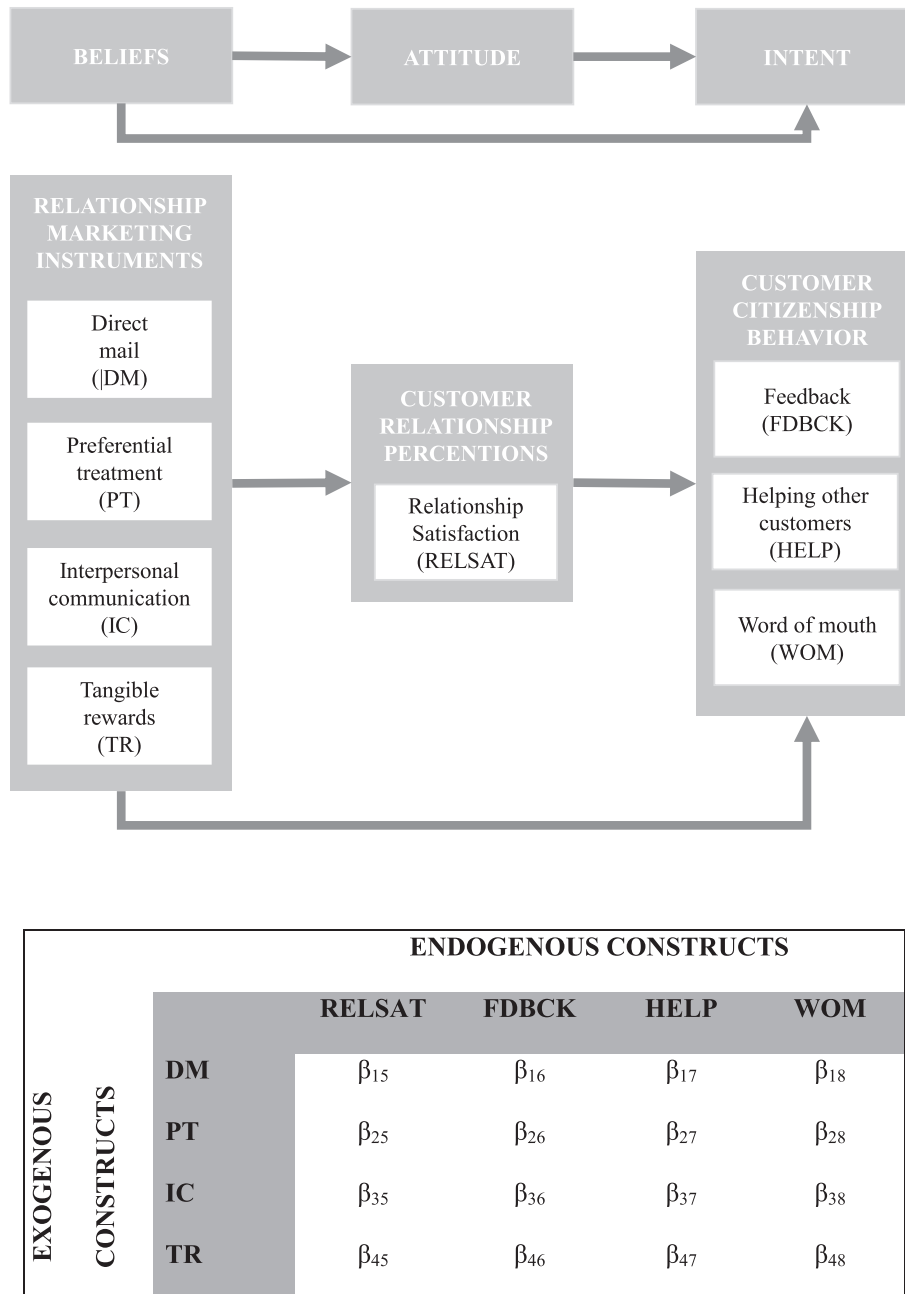


Fig. 1. Conceptual model empirical illustration.

effects are being increasingly *discussed*. This is not surprising as it is in line with the notion of sound yet actionable management research (Kenworthy & Verbeke, 2015) as well as evidence-based management (Albers, 2010; Rousseau, 2012).

With the exception of mediating variables, hypotheses regarding direct effects are typically lacking (see also PLS-SEM applications by Becker et al. (2012) in management and Höck, Ringle, and Sarstedt (2010) and Völckner, Sattler, Hennig-Thurau, and Ringle (2010) in related fields). Regardless of the issue as to whether formal substantive hypotheses about non-direct effects are necessary, assessing whether non-direct effects are statistically significant is relevant as it contributes to effective management practice (Henseler, Ringle, & Sarstedt, 2012; Höck et al., 2010) as well as valuable theoretical insights (Preacher & Hayes, 2008).

Second, many of the reported PLS-SEM applications (92.3%) contain endogenous constructs that are a function of at least two different other constructs. It may be of theoretical and practical relevance to make formal comparisons among the relative impacts of different predictors (Albers, 2010; Preacher & Hayes, 2008). However, none of the reported PLS-SEM applications performed such hypothesis tests. At most, tentative statements are made, such as “seems to have a larger impact than,” which implies that comparisons are indeed considered by researchers. Regarding the relevance of a more formal assessment of the relative impact of constructs, a similar line of reasoning as outlined above (i.e., non-direct effects) applies.

Finally, all PLS-SEM applications (100%) report the amount of variance explained for each endogenous construct (i.e., coefficient

of determination or  $R^2$ ). In contrast, a large majority of PLS-SEM applications (84.6%) do not assess whether the coefficient of determination is significantly different from zero. Rather, researchers rely on rules of thumb, such as  $R^2$  values of 0.67, 0.33, and 0.19 for endogenous constructs can be considered as, respectively, strong, moderate, and weak (cf. Chin, 1998) or Falk and Miller's (1992) suggestion that a cut-off value of 0.10 can be used to decide whether an endogenous construct is adequately explained by a set of exogenous constructs.

In response to these observations, Sections 3.3–3.6 explain how bias-corrected percentile bootstrap confidence intervals can be used to formally assess, respectively, direct effects, non-direct effects, comparison of effects, and the coefficient of determination. Before that, Section 3.2 introduces the empirical example that will be used to illustrate the various procedures.

### 3.2. Empirical illustration

The empirical illustration's conceptual model, which is discussed in the remainder of this section, is outlined below in Fig. 1.

Data were collected from among customers of a Flemish telecom provider (effective  $n = 268$ ) using an online questionnaire. All constructs were measured using validated scales. To assess the scales' psychometric properties we relied on the approach outlined by Leroi-Werelds, Streukens, Brady, and Swinnen (2014). All scales possessed good psychometric properties. SmartPLS 3 (Ringle et al., 2015) was used to estimate the measurement and structural model parameters and to generate the accompanying bootstrap estimates ( $J = 10,000$ ; no sign changes). Bias-corrected percentile confidence intervals were constructed to test the relevant hypotheses. Further details concerning the empirical illustration are available upon request from the first author.

Appendix A offers a concise step-by-step guide on how to construct bias-corrected percentile bootstrap confidence intervals for all types of situations described below. Again, all data and bootstrap output are available upon request from the first author.

### 3.3. Testing direct effects

A direct effect is the hypothesized relationship between two constructs, which most probably reflects the most common situation for hypothesis testing in a PLS-SEM application. The bootstrap output contains  $J$  estimates for each of these direct effects on which the procedures outlined in Table 2 can be readily applied. Although research hypotheses are typically related to structural model parameters, it should be noted that the hypothesis testing procedure for direct effects also applies to assessing the statistical significance of measurement model parameters.

### 3.4. Testing non-direct effects

Based on the bootstrap estimates for the direct relationships, confidence intervals can be constructed for non-direct relationships, such as indirect effects and total effects. In general terms, an indirect effect of latent construct  $k$  on latent construct  $l$ , denoted by  $\rho_{kl}$ , can be computed as the product of the model coefficients accompanying the paths connecting latent construct  $k$  to latent construct  $l$  (denoted by  $w_{ij}$ ). Equation (4) compactly summarizes this idea:

$$\rho_{kl} = \left( \prod_{(LV_k, LV_l) \in P} w_{ij} \right) \quad (4)$$

In terms of the model presented in Fig. 1, the indirect path from

direct mail (DM) to word of mouth (WOM) via relationship satisfaction (RELSAT) equals  $\rho_{18} = \beta_{15} * \beta_{58}$ . As the original bootstrap output contains  $J$  estimates for  $\beta_{15}$  and  $\beta_{58}$ ,  $J$  estimates of parameter  $\rho_{18}$  indicating the designated indirect effect can be calculated. Based on the resulting empirical distribution of these calculated  $\rho_{18}$  parameters, a bootstrap confidence interval can be constructed following the procedures outlined in Table 2.

Besides indirect effects, bootstrap confidence intervals can also be constructed for so-called total effects. Assuming a non-recursive (acyclic) structural model, let parameter  $\delta_{kl} (k \neq l)$  reflect the total effect of latent construct  $k$  on latent construct  $l$ . Thus, parameter  $\delta_{kl}$  reflects the entire set of relationships in a structural model connecting latent construct  $k$  to latent construct  $l$ . Parameter  $\delta_{kl}$  can be calculated from the empirical results describing the set of relationships connecting latent construct  $k$  to latent construct  $l$ , as shown below in equation (5):

$$\delta_{kl} = \sum_{P: (LV_k \rightarrow LV_l)} \left( \prod_{(LV_k, LV_l) \in P} w_{ij} \right) \quad (5)$$

In equation (5),  $w_{ij}$  are the structural model coefficients belonging to the paths that connect latent construct  $k$  to latent construct  $l$ . In words, equation (5) states that the total effect of construct  $k$  on construct  $l$  can be computed by calculating the product of the structural model coefficients  $w_{ij}$  belonging to each of the separate direct relationships connecting construct  $k$  and construct  $l$  and subsequently summing these products over all relevant paths connecting construct  $k$  and construct  $l$ .

In terms of the conceptual model presented in Fig. 1, the total effect of DM on WOM, denoted by  $\delta_{18}$ , equals  $\beta_{15}\beta_{58} + \beta_{18}$ . To assess the statistical significance of the total effects, the procedures outlined in Table 2 must be applied to the distribution of the  $J$  estimates for  $\delta_{18} = \beta_{15}\beta_{58} + \beta_{18}$ , which follows from the bootstrap estimates of the individual structural model parameters involved (i.e., original bootstrap output containing the bootstrap estimates on the direct effects).

In terms of a chain of effects, the idea expressed in equation (5) can also be extended to include measurement model parameters for formative exogenous constructs and reflective endogenous constructs. To illustrate this, consider the part of our model related to the direct and indirect relationships between DM (formative construct) and WOM (reflective construct), as presented in Fig. 2.

A change in formative indicator results in a change in the construct (cf. Jarvis, MacKenzie, & Padsakoff, 2003), and this ignites a chain of effects as implied by the inter-construct nomological web in which the particular construct acts as a predictor. Therefore, the measurement model parameter associated with the relationship between the formative indicator and this construct can therefore be considered to be a part of the entire chain of effects connecting that formative indicator to subsequent constructs. In a similar vein, an endogenous construct's reflective indicator can also be considered to be part of such a chain of effects. That is, as the change in a reflectively modeled construct results in a change of its indicators (cf. Jarvis et al., 2003), the chain of effects leading to the change in a particular reflective endogenous construct extends to this construct's indicators. For a general discussion about the modeling issues associated with endogenous formative variables, and therefore the limitations to extend the principles of equation (5) to this type of variable, the interested reader is referred to the work of Cadogan and Lee (2013).

For example, the total impact of DM's formative indicator  $dm01$  on the WOM's reflective indicator  $wom01$  equals  $(\lambda_{11}\beta_{18}\lambda_{81}) + (\gamma_{11}\beta_{15}\beta_{58}\gamma_{81})$ .

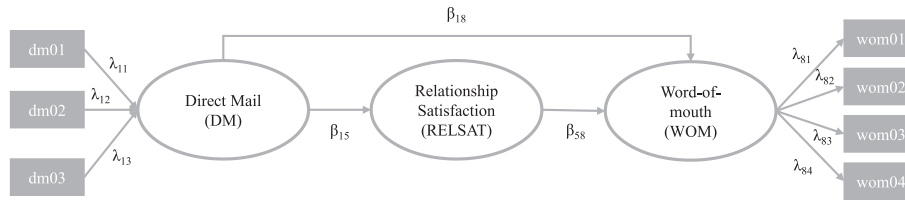


Fig. 2. Non-direct effects and measurement model parameters.

3.5. Comparison of coefficients

Based on the original bootstrap output, bootstrap confidence intervals can be constructed to formally assess whether the relative magnitudes of coefficients are statistically equal. In terms of the empirical illustration, this could involve testing whether the effects of DM and PT on RELSAT are equal.

Following the work of Preacher and Hayes (2008), this implies testing whether the difference between two coefficients, say  $\beta_i$  and  $\beta_j$ , is equal to zero (i.e.,  $H(0): \phi_{ij} = \beta_i - \beta_j = 0$ ). Based on the original bootstrap output containing  $J$  estimates of both  $\beta_i$  and  $\beta_j$ , the difference between the involved coefficients is determined, resulting in  $J$  values for  $\phi_{ij}$ . Subsequently, based on the distribution of parameter  $\phi_{ij}$ , bootstrap confidence intervals using the procedures outlined in Table 2 can be constructed to formally test this hypothesis. Furthermore, it should be noted that the comparison of coefficients is not limited to contrasting only direct effects. A similar procedure can be used to compare non-direct effects. For example, comparing the total effects of DM and PT on HELP boils down to testing  $((\beta_{15} \cdot \beta_{57}) + \beta_{17}) - ((\beta_{25} \cdot \beta_{57}) + \beta_{27}) = 0$ .

Finally, if one is interested in comparing more than two effects, one must account for the multiple testing problem, or equivalently control the family-wise error rate, by applying a Bonferroni-type correction (see also Neter, Kutner, Nachtsheim, and Wasserman (1996) for an excellent treatment of these topics).

3.6. Statistical significance of the coefficient of determination

In a call for accompanying the coefficient of determination with a measure of precision, Ohtani (2000) drew attention to the virtues of bootstrapping. To formally assess whether an endogenous construct's  $R^2$  value is significantly different from zero in a PLS-SEM context, bootstrap confidence intervals, as outlined in Table 2, can be constructed around the estimated  $R^2$  value. In doing so,

Tenenhous, Vinzi, Chatelin, and Lauro's (2005) formula to compute an endogenous construct's coefficient of determination plays a pivotal role, as shown in equation (6):

$$R^2 = \sum_j |\hat{\beta}_j \text{cor}(\eta_i, \xi_j)| \tag{6}$$

Here,  $\beta_j$  is the structural model parameter describing the relationship between  $\xi_j$  and  $\eta_i$ , whereas  $\text{cor}(\eta_i, \xi_j)$  is the (latent variable) correlation between these two constructs.

To construct a bootstrap confidence interval for the coefficient of determination, the following steps must be taken: Use the estimation results from each of the  $J$  bootstrap samples and the latent variable correlations in combination with equation (6) to create  $J$  values of the coefficient of determination. Then, based on these  $J$  coefficients of determination, construct a bias-corrected percentile bootstrap confidence interval using the procedures listed in Table 2.

As can be seen in equation (6), it is possible to increase the coefficient of determination by simply adding exogenous constructs. This of course compromises the principle of model parsimony. Similar to regular regression analysis, it is possible in the case of PLS-SEM to calculate the adjusted coefficient of determination ( $\bar{R}^2$ ), which introduces a penalty for the inclusion of each additional exogenous construct to the structural equation. Equation (7) shows that the adjusted coefficient of determination can be easily derived from the regular coefficient of determination, which is described above:

$$\bar{R}^2 = 1 - \frac{n-1}{n-k} (1 - R^2) \tag{7}$$

In equation (7),  $R^2$  is the coefficient of determination,  $n$  is the sample size, and  $k$  represents the number of exogenous constructs hypothesized to explain an endogenous construct. Also, for the adjusted coefficient of determination, a bootstrap confidence

Table 3  
PLS-SEM bootstrap recommendations.

Topic	Recommendation	References
Resampling method	Bootstrapping is preferred over jackknifing	Efron and Tibshirani (1994) Sahinler and Topuz (2007) Andrews and Buchinsky (2000, 2001, 2002)
Number of bootstrap samples	At least 10,000	
Size bootstrap samples	Equal to the size of the original sample (i.e., number of valid observations or effective sample size)	Hair et al. (2011)
Parameter evaluation	Bias-corrected percentile bootstrap confidence intervals are preferred over regular percentile and standard normal bootstrap confidence intervals and bootstrap p-values	MacKinnon et al. (2004) Williams and MacKinnon (2008) Wood (2005)
Software setting (SmartPLS 3)	No sign change option Bias-corrected and accelerated (BCa) bootstrap (this constructs the bias-corrected percentile confidence intervals discussed in this paper)	Hair, Hult, Ringle, and Sarstedt (2013)
Reporting	All of the elements mentioned in this table as well as the statistic being tested and the significance level	



interval can be constructed (cf. Ohtani, 2000). In this case, the  $J$  values for  $R^2$  provide the necessary input.

In terms of our empirical illustration, the coefficient of determination for RELSAT equals  $(\beta_{15} \cdot \text{corr}(LV_1, LV_5) + \beta_{25} \cdot \text{corr}(LV_2, LV_5) + \beta_{35} \cdot \text{corr}(LV_3, LV_5) + \beta_{45} \cdot \text{corr}(LV_4, LV_5))$ . Note that the latent variable correlations are not available for each bootstrap sample when using standard PLS-SEM software. Here the values for the original sample are used for calculating all  $J$  coefficients of determination. To arrive at the adjusted coefficient of determination, equation (7) must be applied. For the current situation,  $n$  equals 268 and  $k$  equals 3.

#### 4. Conclusion

According to Chia (2014), conducting relevant and rigorous European management research requires researchers “to imaginatively seek out ever-newer meanings to both exceptional and ordinary everyday experiences, familiar and unfamiliar happenings, and taken-for-granted conceptual formulations” (Chia, 2014, p. 686). PLS-SEM’s exploratory characteristic perfectly fits this point of view and can therefore be considered a valuable data analytical approach for European management researchers.

From a statistical explanatory modeling point of view, hypothesis testing is a critical element in developing relevant and rigorous theory (Shmueli & Koppius, 2011). In a PLS-SEM context, hypothesis testing relies on bootstrapping. As evidenced by the overview of PLS-SEM applications in European management research (see also Table 1), the accompanying bootstrap procedures are often suboptimal. In response to this observation, this paper provides a detailed overview of how to construct bias-corrected percentile bootstrap confidence intervals and to demonstrate how these bootstrap confidence intervals can be used to test hypotheses related to frequently encountered research situations in management research. Although not directly related to a particular substantive European management research domain, this paper contributes to the European management research domain in the following ways.

First, a key recommendation of our work is that in order to make better statistical inferences, which is one cornerstone of (European) management research (Cashen & Geiger, 2004; Thietart, 2001), constructing bias-corrected percentile bootstrap confidence intervals based on a large number of bootstrap samples (i.e., at least 10,000) offers a powerful approach to test a large variety of hypotheses. In terms of practical implementation, Table 3 presents a set of guidelines and minimal requirements for PLS-SEM bootstrap procedures that are relevant to researchers, editors, and reviewers alike.

Second, as evidenced by the work of Hair et al. (2012), models in management research become more and more complex, thereby increasing the likelihood of non-direct effects (i.e., indirect and total effects) as well as the need to compare these effects. In line with Chia’s (2014) call to be “empirically sensitive and to adopt a syncretistic approach” (p. 688) to understanding phenomena, formally assessing the statistical significance of non-direct effects as well as formally comparing the magnitude of effects will contribute to the development of relevant and rigorous European management theory.

Third, a model’s explanatory power, which is another core element in explanatory statistical modeling (Shmueli & Koppius, 2011), can be evaluated empirically by assessing the significance and magnitude of the coefficient of determination (i.e.,  $R^2$ ). Although  $R^2$  values of endogenous constructs are typically reported in a PLS-SEM application, the accompanying evaluation of the  $R^2$  value is generally done based on simple heuristics. By demonstrating how to formally assess the significance of an  $R^2$  value, our

work therefore takes an important step in evaluating, according to Kenworthy and Verbeke (2015), one of the key characteristics of truly valuable European management theory: explanatory capacity.

#### 5. Prediction: bootstrapping and cross validation<sup>2</sup>

As already mentioned at the start, the emphasis of the current paper is on explanatory modeling. It should be noted that explanatory power does not imply predictive power (Shmueli & Koppius, 2011; Shmueli, 2010). As such, the need for explicit assessment of predictive power is strongly emphasized in recent PLS-SEM publications (e.g., Cepeda Carrión, Henseler, Ringle, & Roldán, 2016; Evermann & Tate, 2016; Shmueli, Ray, Velasquez-Estrada, & Chatla, 2016).

The central tenet of assessing predictive power focuses on the model’s ability to generate accurate predictions of new observations (i.e., out-of-sample predictions). According to Harrell (2001), so-called internal validation is the preferred approach in validating a model’s predictive performance. Departing from a single dataset, internal validation involves using one set of subjects to estimate the model parameters (i.e., training sample) and subsequently using these parameter estimates to validate the model’s performance on a set of different subjects (i.e., validation sample). One method that is particularly relevant and useful in this respect is cross validation.

Cross validation is a resampling procedure used to obtain nearly unbiased estimates of model performance without sacrificing the sample size. Wold (1982) advocated the use of K-fold cross-validation or blindfolding procedures to assess the model’s predictive relevance. In K-fold cross validation, the original dataset is randomly partitioned into K equal-sized subsets. Of these K subsets, a single subset is used as a validation sample, whereas the other K–1 subsets are put together and are used as a training sample. These procedures are repeated K times so that each K subset acts as a validation sample. Finally, the K results are then combined to produce a single estimation (see also Tenenhaus et al., 2005). With regard to K, a value from 5 to 10 has been proven to be feasible given a sufficient sample size (Chin, 1998).

So how does this relate to this paper’s focus on improved bootstrap procedures for testing hypotheses (i.e., explanatory modeling) in a PLS-SEM context? Consistent with the work of Shmueli and Koppius (2011), who suggested evaluating a model’s predictive power even if the main aim of the modeling is explanatory, employing both the bootstrap procedures suggested in this paper as well as a cross-validation procedure to validate the model may lead to a more comprehensive and insightful model evaluation. Not only is this especially valuable given PLS-SEM’s prediction-oriented nature (Cepeda Carrión et al., 2016), it is also pivotal in the pursuit of Chia’s (2014) “scholarship of common sense,” as the evaluation of predictive performance contributes to the developing of new theory, developing and evaluating as well as improving construct operationalization, comparing theories, improving existing theory, assessing relevance, and evaluating the predictability of phenomena (Shmueli & Koppius, 2011; Shmueli et al., 2016).

#### 6. Limitations

In this paper, the focus is on a limited set of bootstrap confidence intervals. It was deliberately chosen to focus on those bootstrap

<sup>2</sup> We would like to thank the anonymous reviewer for bringing this point to our attention.

confidence intervals that can be constructed by the researcher using the bootstrap output from standard PLS-SEM software. However, more bootstrap procedures, such as the double bootstrap and the 0.632 bootstrap, are available that might outperform the ones presented in this paper. Regarding these advanced bootstrap procedures in a PLS-SEM context, more academic research and the development of user-friendly software applications are needed.

#### Appendix A. Constructing bias-corrected percentile bootstrap confidence intervals step by step

This appendix provides a detailed, step-by-step explanation of

corrected percentile bootstrap confidence interval in Excel. The original bootstrap output, as generated by SmartPLS 3 (Ringle et al., 2015), starts in row 23. Rows 1–18 show the actual construction of the bootstrap confidence interval and are based on equations (3a)–(3e) presented in Table 2 of the paper. Note that the procedure outlined below boils down to the construction of bias-corrected bootstrap confidence intervals for direct effects (i.e., both structural and measurement model parameters). Furthermore, this general procedure forms the basis for all other bootstrap confidence intervals discussed in this paper.

Exhibit A1: Bias-corrected percentile bootstrap confidence interval's direct effect (general procedure).

	A	B	C	D	E
1		FB01	MD^3	MD^2	OSE
2	Original sample estimate	0,654			
3	Mean	0,651			
4	Sum		0,735	30,110	
5	Accel denom			991,324	
6	Acceleration coeff	0,001			
7	Percentage				0,484
8	Z(0)				-0,041
9	Z-lower	-1,96			
10	Z-upper	1,96			
11	Z-lower prime	-2,039			
12	Z-upper prime	1,881			
13	p-lower prime	0,021			
14	p-upper prime	0,970			
15	Observation lower bound	207			
16	Observation upper bound	9700			
17	CI lower bound	0,529			
18	CI upper bound	0,745			
19					
20	<b>Bootstrap samples (J = 10,000)</b>				
21					
22		FB01	MD^3	MD^2	OSE
23	Sample 0	0,671	-7,54534E-06	0,000385	0
24	Sample 1	0,647	8,43908E-08	1,92E-05	1
25	Sample 2	0,685	-3,79795E-05	0,00113	0
26	Sample 3	0,757	-0,001178042	0,011154	0
10017	Sample 9994	0,735	-0,000584564	0,006991	0
10018	Sample 9995	0,686	-4,1471E-05	0,001198	0
10019	Sample 9996	0,62	3,09186E-05	0,000985	1
10020	Sample 9997	0,588	0,000254675	0,004018	1
10021	Sample 9998	0,692	-6,69912E-05	0,001649	0
10022	Sample 9999	0,735	-0,000584564	0,006991	0

the construction of bias-corrected percentile bootstrap confidence intervals for direct effects, non-direct effects, coefficient of determination, and the comparison of coefficients. The construction of the confidence intervals was done using Excel. The bootstrap output used in this appendix as well as the original data are available upon request from the first author. Readers who are interested in the theoretical background as well as details pertaining to the accompanying empirical study can also request more information on this from the first author.

#### General procedure (direct effects)

Exhibit A1 provides an overview of the construction of the bias-

*Step-by-step instructions to construct bias-corrected percentile bootstrap confidence intervals.*

#### Step 1: Preparing the Excel worksheet.

##### Step 1.1: Copying the bootstrap output into Excel.

The bootstrap output was generated in SmartPLS 3 and were copied into an Excel worksheet (via "export to clipboard/CSV" in the SmartPLS 3 program). The bootstrap output consists of a row containing the labels (see row 1 in Exhibit A1) and column containing J bootstrap estimates for each variable (starts in row 23 of Exhibit A1).

##### Step 1.2: Adding columns.

For each variable, three additional columns were added: MD<sup>3</sup>, MD<sup>2</sup>, and OSE. Furthermore, at the top of the worksheet, a number

of rows (i.e., 21) were inserted for the calculations needed to construct the bias-corrected bootstrap confidence intervals. The names of these additional rows and columns are inserted manually.

*Step 1.3: Adding rows.*

The figures in row 2 (i.e., original sample estimates) stem from the SmartPLS 3 calculation results and are copied in the Excel worksheet from the SmartPLS 3 output. All other figures in the columns and rows inserted in step b are inserted manually or calculated based on the bootstrap data.

*Note: it is possible to hide the entire midsection of the bootstrap output while performing all calculations. The key advantage is that you do not have to scroll through the entire list of bootstrap estimates.*

**Step 2: The acceleration coefficient.**

Calculating the acceleration coefficient that is shown in cell B6 and calculated as shown in equation (3c) in the paper is done via the following substeps:

*Step 2.1: Column MD<sup>3</sup>.*

The column named MD<sup>3</sup> is related to the numerator of equation (3c) in Table 2 and equals the difference between each bootstrap sample's estimate and mean bootstrap estimate raised to the power of 3. The mean bootstrap estimate can be found in cell B3 and is computed as " $= \text{AVERAGE}(B23:B10022)$ ". For bootstrap sample 0 (row 23), the entry for MD<sup>3</sup> equals " $=(B23-B\$3)^3$ ". Apply to all bootstrap samples.

*Step 2.2: Column MD<sup>2</sup>.*

The column named MD<sup>2</sup> is related to the denominator of equation (3c) in Table 2 and equals the difference between each bootstrap sample's estimate and mean bootstrap estimate raised to the power of 2. Again, the mean bootstrap estimate can be found in cell B3. For bootstrap sample 0 (row 23), the entry for MD<sup>2</sup> equals " $=(B23-B\$3)^2$ ". Apply to all bootstrap samples.

*Step 2.3 The sums of MD<sup>3</sup> and MD<sup>2</sup>.*

Finally, the sum of column MD<sup>3</sup> and MD<sup>2</sup> is, respectively, determined. The corresponding sums are then stored in cells C4 ( $=\text{SUM}(C23:C10022)$ ) and D4 ( $=\text{SUM}(D23:D10022)$ ).

*Step 2.4 The actual acceleration coefficient.*

To avoid mistakes, an intermediate step is taken to calculate the denominator of the acceleration coefficient (stored in cell D5). Following equation (3c) of the paper, this boils down to " $= 6*(D4^3/2)$ ". The actual acceleration coefficient (stored in cell B6) now equals " $= C4/D5$ ".

**Step 3: The Z-values and p-values.**

The third step involves the calculation of the various Z-values (rows 8–12) and p-values (rows 13–14) needed in the construction of the confidence interval.

*Step 3.1: Calculating Z(0)*

The value for Z(0), which can be found in cell E8, involves the following steps:

*Step 3.1.1:* The column named "OSE" involves the comparison between each bootstrap sample estimate and the original sample estimate and is needed for the calculation of Z(0). If the bootstrap sample estimate (listed in cells B23–B10022) is smaller than the original sample estimate (cell B2), the corresponding cell in the OSE column is assigned a value of "1," and in all other cases, a value of "0" is assigned. This is easily done by means of the "IF" function in Excel. Thus, for bootstrap sample 0 (row 23), this equals " $= \text{IF}(B23 < B\$2; 1; 0)$ ".

*Step 3.1.2:* Cell E7 reflects the proportion of bootstrap samples for which the estimate was smaller than the original sample estimate and equals " $= \text{SUM}(E23:E10022)/10000$ ".

*Step 3.1.3:* The actual value for Z(0) can be found in cell E8 and is derived from the output obtained in step 3.1.2. In particular, it is equal to " $= \text{NORM.S.INV}(E7)$ ".

*Step 3.2: Calculating Z-lower prime and Z-upper prime.*

The values for Z-lower prime (see also equation (3a) in Table 2) and Z-upper prime (see also equation (3b) in Table 2) are stored in cells B11 and B12, respectively.

*Step 3.2.1:* The values for Z-lower (cell B9) and Z-upper (cell B10) are manually inserted. Note that their values depend on the significance level the researcher wants to employ. In the case of a 95% (90%) confidence interval, Z-lower (i.e.,  $Z_{LB}$ ) and Z-upper (i.e.,  $Z_{UB}$ ) are  $-1.96$  ( $-1.645$ ) and  $1.96$  ( $1.645$ ), respectively.

*Step 3.2.2:* Using the acceleration coefficient (cell B6), the Z(0) value (cell E8), and the value for Z-lower (cell B9), the value for Z-lower prime (cell B11) is calculated as implied by equation (3a) in Table 2. For the situation at hand, this equals " $= E8+((E8+B9)/(1-(B6*(E8+B9))))$ ".

*Step 3.2.3:* Using the acceleration coefficient (cell B6), the Z(0) value (cell E8), and the value for Z-upper (cell B10), the value for Z-upper prime (cell B12) is calculated as implied by equation (3b) in Table 2. For the situation at hand, this equals " $= E8+((E8+B10)/(1-(B6*(E8+B10))))$ ".

*Step 3.3: The p-values accompanying the Z-prime values.*

To arrive at the p-values associated with the Z-prime values determined in step 3.2.2 (i.e., Z-lower prime) and step 3.2.3 (i.e., Z-upper prime), the "NORM.S.DIST" function in Excel is used.

*Step 3.3.1:* The p-value associated with Z-lower prime (i.e., p-lower prime in cell B13) equals " $= \text{NORM.S.DIST}(B11, \text{TRUE})$ ".

*Step 3.3.2:* The p-value associated with Z upper prime (i.e., p-lower prime in cell B14) equals " $= \text{NORM.S.DIST}(B12, \text{TRUE})$ ".

**Step 4: Determining the bounds of the confidence interval.**

This fourth and final step in the construction of the bias-corrected percentile bootstrap confidence intervals consists of the following two substeps:

*Step 4.1: Observation numbers.*

The observation number that corresponds to the lower and upper bounds of the confidence interval is derived by multiplying the respective p-values with the number of bootstrap samples.

*Step 4.1.1:* Observation number reflecting the lower bound can be in cell B15 and equals " $= B13*10,000$ ".

*Step 4.1.2:* Observation number reflecting the upper bound can be in cell B16 and equals " $= B14*10,000$ ".

*Step 4.2: The bounds.*

The final step is to determine which parameter estimates correspond to the observation numbers obtained in the previous step.

*Step 4.2.1:* The parameter estimate marking the lower bound of the confidence interval can be found in cell B17 and equals " $= \text{SMALL}(B23:B10022; B15)$ ".

*Step 4.2.2:* The parameter estimate marking the upper bound of the confidence interval can be found in cell B18 and equals " $= \text{SMALL}(B23:B10022; B16)$ ".

*Non-direct effects*

The construction of the bias-corrected bootstrap confidence interval for indirect effects is demonstrated below for the indirect effect from IC on FDBCK via RELSAT. The bootstrap estimates for the involved direct effects (i.e., the relationships "IC-RELSAT" (Exhibit A2 cell B23 and below) and "RELSAT-FDBCK" (Exhibit A2 cell C23

and below)) are the starting point. Furthermore, the original sample estimates for these direct relationships are recorded from the SmartPLS 3 output (Exhibit A2 cells B2 and C2, respectively).

Exhibit A2: Bootstrap confidence interval's non-direct effects.

containing the R<sup>2</sup> values of the bootstrap samples after the following preparatory steps are taken. These preparatory steps are outlined below for the construct “RELSAT” (see also Exhibit A3).

	Input for indirect effect			Bias-corrected bootstrap confidence interval				
	IC-RELSAT	RELSAT-FEEDBACK		IC-RELSAT-FEEDBACK	MD^3	MD^2	OSE	
1								
2	Original sample estimates	0,292	0,190	Original sample estimate	0,05548			
3	Mean	0,291	0,188	Mean	0,054			
4				Sum		-0,040	6,818	
5				Accel denom			106,820	
6				Acceleration coeff	0,000			
7				Percentage				
8				Z(0)			0,538	
9				Z-lower	-1,96		0,094	
10				Z-upper	1,96			
11				Z-lower prime	-1,773			
12				Z-upper prime	2,147			
13				p-lower prime	0,038			
14				p-upper prime	0,984			
15				Observation lower bound	381			
16				Observation upper bound	9841			
17				CI lower bound	0,011			
18				CI upper bound	0,113			
19								
20	Bootstrap results relevant direct effects (J = 10,000)			Bootstrap samples (J = 10,000)				
21								
22	IC-RELSAT	RELSAT-FEEDBACK		IC-RELSAT-FEEDBACK	MD^3	MD^2	OSE	
23	Sample 0	0,241	0,171	Sample 0	0,041211	2,26359E-06	0,000172398	1
24	Sample 1	0,311	0,084	Sample 1	0,026124	2,24664E-05	0,000796201	1
25	Sample 2	0,279	0,159	Sample 2	0,044361	9,94023E-07	9,96011E-05	1
26	Sample 3	0,298	0,175	Sample 3	0,05215	1,05184E-08	4,80064E-06	1
10017	Sample 9994	0,242	0,273	Sample 9994	0,066066	-1,61189E-06	0,000137475	0
10018	Sample 9995	0,298	0,247	Sample 9995	0,073606	-7,14998E-06	0,000371139	0
10019	Sample 9996	0,302	0,237	Sample 9996	0,071574	-5,11776E-06	0,000296975	0
10020	Sample 9997	0,305	0,142	Sample 9997	0,04331	1,3423E-06	0,000121684	1
10021	Sample 9998	0,215	0,162	Sample 9998	0,03483	7,42747E-06	0,00038068	1
10022	Sample 9999	0,337	0,225	Sample 9999	0,075825	-9,91615E-06	0,000461561	0

To construct the actual bias-corrected bootstrap confidence interval for the indirect effect, the same procedure as outlined above for the confidence intervals of the direct effects needs to be followed, but then on the bootstrap estimates for the relevant indirect effect. For the situation at hand, this is shown in Exhibit A2 columns D–H). In order to construct the relevant confidence interval, the following needs attention:

- The figures in column E under “IC-RELSAT-FDBCK” present the product of the involved direct effects for each bootstrap sample (cf. equation (4) in the paper) and represent the data on the confidence interval to be constructed.
- The original sample estimated (cell E2 and colored black) is not copied from the SmartPLS output, but is the product of the original sample estimates of the involved direct effects (i.e., Cell E2 equals “ = B2\*C2”).

Note that if one is interested in assessing the significance of a total effect a similar procedure applies, yet the data column on which the bootstrap confidence interval is to be constructed must reflect the total effect adequately as implied by equation (5) in the paper.

Coefficient of determination

To calculate the bias-corrected confidence interval for an endogenous construct’s coefficient of determination, equation (6) plays a pivotal role. To construct this confidence interval, the general procedure (see above) must be performed on a data column

- Calculate the R<sup>2</sup> value for each bootstrap sample according to equation (6). The inputs for this are bootstrap coefficients associated with the direct relationships (i.e., columns B, D, F, and H cell 24 and below) and the latent variable correlations (i.e., cells B4, D4, F4, and H4, which are shaded gray). These latent variable correlations are equal for each bootstrap sample and stem from SmartPLS 3 calculation results.
- The calculation of the R<sup>2</sup> values is done in stages. That is, per exogenous construct the product of the parameter accompanying its link to the endogenous construct and the corresponding latent variable correlation is calculated. The results of these calculations are listed in columns C, E, G, and I in cell 24 and below. So, for bootstrap sample 0 (row 24), this leads to cell C24 being equal to “ = ABS(B\$4)\*ABS(B24)” and so forth.
- To arrive at the column containing the data on which the confidence interval is to be constructed (i.e., column K cell 24 and below), the different products are summed. Thus, in terms of bootstrap sample 0, the bootstrap R<sup>2</sup> value (i.e., cell K24) corresponds to “ = C24 + E24 + G24 + I24”.
- The original sample estimate for the R<sup>2</sup> value (cell K3) is calculated in a similar fashion as the R<sup>2</sup> values for the bootstrap samples, but then using the original sample estimates that are obtained from the SmartPLS 3 output (see also Exhibit A3, specifically the gray cells in row 5).

Exhibit A3: Construction bootstrap confidence interval coefficient of determination.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Calculation coefficient of determination (R2) - Original sample									Bias-corrected bootstrap confidence interval				
2		DM-RELSAT	R2-DM	IC-RELSAT	R2-IC	PT-RELSAT	R2-PT	TR-RELSAT	R2-TR	Original sample estimate	R2-RELSAT	MD^3	MD^2	OSE
3										Mean	0,546			
4	Correlation with DV	0,444		0,606		-0,420		0,651		Sum	0,545			
5	Original sample estimates	0,179	0,079	0,292	0,177	-0,168	0,071	0,337	0,219			0,011		3,023
6										Accel denom				31,529
7										Acceleration coeff	0,000			
8										Percentage				
9										Z(0)				0,511
10										Z-lower	-1,96			0,028
11										Z-upper	1,96			
12										Z-lower prime	-1,902			
13										Z-upper prime	2,018			
14										p-lower prime	0,029			
15										p-upper prime	0,978			
16										Observation lower bound	286			
17										Observation upper bound	9782			
18										CI lower bound	0,511			
19										CI upper bound	0,579			
20	Calculation coefficient of determination (R2) - Bootstrap sample									Bootstrap samples (J = 10,000)				
21		DM-RELSAT	R2-DM	IC-RELSAT	R2-IC	PT-RELSAT	R2-PT	TR-RELSAT	R2-TR		R2-RELSAT	MD^3	MD^2	OSE
22														
23														
24	Sample 0	0,247	0,110	0,241	0,146	-0,258	0,108	0,286	0,186	Sample 0	0,55026	-1,1719E-07	2,39474E-05	0
25	Sample 1	0,204	0,091	0,311	0,188	-0,152	0,064	0,306	0,199	Sample 1	0,542088	3,52355E-08	1,07478E-05	1
26	Sample 2	0,196	0,087	0,279	0,169	-0,203	0,085	0,352	0,229	Sample 2	0,57051	-1,58958E-05	0,000632201	0
27	Sample 3	0,147	0,065	0,298	0,181	-0,011	0,005	0,479	0,312	Sample 3	0,562305	-4,85997E-06	0,000286917	0
10018	Sample 9994	0,161	0,071	0,242	0,147	-0,141	0,059	0,406	0,264	Sample 9994	0,541662	5,08334E-08	1,37225E-05	1
10019	Sample 9995	0,134	0,059	0,298	0,181	-0,198	0,083	0,276	0,180	Sample 9995	0,50292	7,64755E-05	0,001801696	1
10020	Sample 9996	0,159	0,071	0,302	0,183	-0,155	0,065	0,401	0,261	Sample 9996	0,579759	-4,06814E-05	0,001182852	0
10021	Sample 9997	0,168	0,075	0,305	0,185	-0,237	0,100	0,295	0,192	Sample 9997	0,551007	-1,79465E-07	3,18165E-05	0
10022	Sample 9998	0,237	0,105	0,215	0,130	-0,304	0,128	0,252	0,164	Sample 9998	0,52725	5,94586E-06	0,000328203	1
10023	Sample 9999	0,202	0,090	0,337	0,204	-0,216	0,091	0,273	0,178	Sample 9999	0,562353	-4,9014E-06	0,000288545	0

Comparing coefficients

Exhibit A4 shows the construction of a bias-corrected percentile bootstrap confidence interval concerning the null hypothesis that DM and IC have an equal effect on RELSAT. Again, the general procedure outlined above takes central stage. For the situation at hand, the confidence interval is constructed as follows:

- Columns B and C (rows 24 and below) contain the bootstrap estimates for the effects to be compared.

- Cells B4 and C4 contain the original sample estimates copied from the SmartPLS 3 output.
- Column E (cell 24 and below) contains the differences between the coefficients involved. For bootstrap sample 0 (cell E24), this equals “ = B24–C24amprdqusemicolon
- The confidence interval is created using the data in column E (cell 24 and below).

Exhibit A4: Bootstrap confidence interval's comparison of effects.

	A	B	C	D	E	F	G	H
1	Comparison of coefficients				Bias-corrected bootstrap confidence interval			
2					DM vs IC	MD^3	MD^2	OSE
3		DM-RELSAT	IC-RELSAT	Original sample estimate	-0,113			
4	Original sample estimates	0,179	0,292	Mean	-0,112			
5				Sum		-0,136	70,151	
6				Accel denom			3525,362	
7				Acceleration coeff	0,000			
8				Percentage				0,496
9				Z(0)				-0,009
10				Z-lower	-1,96			
11				Z-upper	1,96			
12				Z-lower prime	-1,979			
13				Z-upper prime	1,941			
14				p-lower prime	0,024			
15				p-upper prime	0,974			
16				Observation lower bound	239			
17				Observation upper bound	9739			
18				CI lower bound	-0,277			
19				CI upper bound	0,050			
20	Comparison of coefficients				Bootstrap samples (J = 10,000)			
21								
22		DM-RELSAT	IC-RELSAT		DM vs IC	MD^3	MD^2	OSE
23								
24	Sample 0	0,247	0,241	Sample 0	0,006	-1,38913E-07	2,68222E-05	0
25	Sample 1	0,204	0,311	Sample 1	-0,107	-2,48435E-05	0,000851415	0
26	Sample 2	0,196	0,279	Sample 2	-0,083	-2,48435E-05	0,000851415	0
27	Sample 3	0,147	0,298	Sample 3	-0,151	5,85059E-05	0,001507069	1
10018	Sample 9994	0,161	0,242	Sample 9994	-0,081	-3,03101E-05	0,000972131	0
10019	Sample 9995	0,134	0,298	Sample 9995	-0,164	0,000139161	0,002685414	1
10020	Sample 9996	0,159	0,302	Sample 9996	-0,143	2,92779E-05	0,000949933	1
10021	Sample 9997	0,168	0,305	Sample 9997	-0,137	1,52917E-05	0,000616081	1
10022	Sample 9998	0,237	0,215	Sample 9998	0,022	-0,00241576	0,018004009	0
10023	Sample 9999	0,202	0,337	Sample 9999	-0,135	1,18851E-05	0,000520797	1



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