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Hierarchical Latent Variable Models in PLS-SEM: Guidelines for Using Reflective-Formative Type Models

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Partial least squares structural equation modeling (PLS-SEM), or partial least squares path modeling (PLS) has enjoyed increasing popularity in recent years. In this context, the use of hierarchical latent variable models has allowed researchers to extend the application of PLS-SEM to more advanced and complex models. However, the attention has been mainly focused on hierarchical latent variable models with reflective relationships. In this manuscript, we focus on second-order hierarchical latent variable models that include formative relationships. First, we discuss a typology of (second-order) hierarchical latent variable models. Subsequently, we provide an overview of different approaches that can be used to estimate the parameters in these models: (1) the repeated indicator approach, (2) the two-stage approach, and (3) the hybrid approach. Next, we compare the approaches using a simulation study and an empirical application in a strategic human resource management context. The findings from the simulation and the empirical application serve as a basis for recommendations and guidelines regarding the use and estimation of reflective-formative type hierarchical latent variable models in PLS-SEM.

Introduction

The number of PLS-SEM applications in strategic management compared to disciplines like marketing or management information systems is substantially smaller (Hair et al., 2012). This finding

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is in line with Ketchen et al. (2008), who report that in the strategic management flagship journal, *Strategic Management Journal*, researchers predominantly rely on "first-generation" analysis techniques, such as regression analysis and ANOVA, and only to a limited extent on "second-generation" analysis techniques, such as structural equation modeling (SEM). This tendency might be partly due to the fact that measurement is generally considered to be a low-priority topic for the strategic management field, and is further compounded by the use of single-item measures (Boyd et al., 2005; Podsakoff et al., 2006). Yet, Podsakoff et al. (2006) observe that the strategic management field has increasingly turned towards the development of multi-item scales and the use of SEM. Similarly, Hair et al. (2012) find that the use of PLS-SEM is increasing in the strategic management discipline and is expected to grow in future, following similar developments in other disciplines. Nevertheless, Hair et al. (2012, p. 3) also caution that "*…[strategic management] researchers still often do not fully utilize available analytical potential and sometimes incorrectly apply methods in top-tier strategic management journals*".

Moreover, Podsakoff et al. (2006, p. 198) assess 257 constructs in the strategic management literature and find that "*…many important strategy constructs are more appropriately modeled as having formative indicators than as having reflective indicators*" which might lead to severely biased results (Jarvis et al., 2003). A key factor contributing to the misspecification of measurement models in strategic management research is the omission of explicitly specifying the higher-order dimensionality of the focal construct (Podsakoff et al., 2006). Podsakoff et al. (2006) provide the example of social capital in Koka and Prescott (2002) as a second-order construct consisting of three first-order constructs (information volume, information diversity and information richness). In the original manuscript, Koka and Prescott (2002) modeled social capital as a second-order construct with three reflective first-order constructs, while conceptually a second-order model with three formative first-order constructs would have been more appropriate (cf. Podsakoff et al., 2006).

It should be noted that a key requirement for defining and operationalizing multidimensional constructs is that they should be derived from theory and theory should indicate the number of (sub)dimensions and their relationship to the higher-order construct (Johnson et al., 2012; MacKenzie et al., 2011; Polites et al., 2012). A number of rationales have been brought forward to advocate the use of these hierarchical latent variable models over the use of models consisting solely of lower-order dimensions (e.g., Edwards, 2001; Johnson et al., 2012; Wetzels et al., 2009). Proponents of the use of higher-order constructs have argued that they allow for more theoretical parsimony and reduce model complexity. Moreover, hierarchical latent variable models allow matching the level of abstraction for predictor and criterion variables in conceptual models ("compatibility principle"; Johnson et al., 2012). For example, in organizational behavior, higher-order constructs such as job satisfaction and job performance consisting of multiple dimensions and therefore operating at the same level of abstraction, are often related to each other. In addition, the introduction of hierarchical latent variables in SEM allows for the assessment of reliability, construct validity and nomological validity of the higher-order constructs (Edwards, 2001; Fornell and Larcker, 1981; MacKenzie et al., 2011; Wetzels et al., 2009).[1]

In the context of PLS-SEM models, hierarchical latent variable models have shown an increasing popularity in recent years (Edwards, 2001; Jarvis et al., 2003; Johnson et al., 2012; Polites et al., 2012; Ringle et al., 2012; Wetzels et al., 2009). Both covariance-based structural equation modeling (CB-SEM) and PLS-SEM can be used to estimate the parameters in hierarchical latent variable models (Wetzels et al., 2009). For covariance-based SEM, guidelines and empirical illustrations are generally abundantly available (e.g., Edwards, 2001; Jarvis et al., 2003; Rindskopf and Rose, 1988). For PLS-SEM, guidelines are mainly available for hierarchical latent variable models with reflective relationships (e.g., Lohmöller, 1989; Wetzels et al., 2009; Wold, 1982). However, Ringle et al. (2012) show that hierarchical latent variable models with reflective relationships in the first-order and second-order of the hierarchy represent only a minority (20%) of the models

[1] For more details, we refer to MacKenzie et al. (2011), who provide an integral approach for construct measurement and validation procedures including the treatment of multidimensional constructs.

applied in *MIS Quarterly*. Thus, there is ample need for guidelines on using and modeling hierarchical latent variable models with formative relationships in PLS-SEM, such as the second-order model for social capital by Koka and Prescott (2002) clearly exemplifies.

Two approaches are generally suggested to estimate the parameters in hierarchical latent variable models using PLS-SEM: (1) the repeated indicator approach and (2) the two-stage approach (Ringle et al., 2012; Wetzels et al., 2009). There is only limited evidence of the appropriateness regarding the use of these approaches using PLS-SEM for the different types of hierarchical latent variable models, and consequently Wetzels et al. (2009, p. 191) recommend: "*We would need to explore how this sequential latent variable score method [two-stage approach] compares to the repeated use of manifest variables. Furthermore, we would need to assess the underlying assumptions and guidelines for the use of this approach*". With this paper, we strive to follow this recommendation and assess the performance of both approaches when the higher-order construct is formative. In addition, we also assess a third approach, called the hybrid approach, proposed by Wilson and Henseler (2007) that has not yet received a lot of attention in the PLS-SEM literature.[2]

Although formative type hierarchical latent variable models are often employed in empirical research, clear guidelines on which approach is most appropriate to model these types of hierarchical latent variables are missing in the literature. This might also be a reason for generally inadequate reporting standards, as Ringle et al. (2012, p. xii) note that only "*…half of the studies explain exactly how they were conducted*". Thus, a more detailed discussion of the typology of hierarchical latent variables is required which also includes an assessment of the approaches to estimate the different types of hierarchical latent variable models with a special focus on hierarchical latent variables where the higher-order constructs are formative. Moreover, guidance on how to report the results of hierarchical latent variables in PLS-SEM is needed to improve the generally unsatisfactory reporting standards identified in the literature (Ringle et al., 2012) and to assure adequate measurement models.

Although we include all types of hierarchical latent variable models in our conceptual framework, we will focus on the reflective-formative hierarchical latent variable model in our simulations and empirical application as it has received only limited attention in the extant PLS-SEM literature, even though it is the most widely used type of model (Ringle et al., 2012). To compare the performance of different approaches available in PLS-SEM to estimate a hierarchical latent variable model, we employ a Monte Carlo simulation. The findings of the Monte Carlo simulation will be further illustrated with an empirical application in the context of strategic human resource management. This complementary approach will allow us to formulate guidelines and recommendations for the use of the different approaches for reflective-formative hierarchical latent variable models in PLS-SEM.

In addition, we will propose a way to assess the effect of antecedent constructs on a formative higher-order construct (which is already fully explained by its lower-order constructs) when using the repeated indicator or hybrid approach. We adapt an idea from Cadogan and Lee (in press), and propose to model the effect of antecedent constructs on formative higher-order constructs through its measures, hence its lower-order constructs. Therefore, not only the two-stage approach, but also the repeated indicator and hybrid approaches are suitable in a complex path model in which the formative hierarchical latent variable has an endogenous position. Taking this into consideration, our simulation results and the empirical application will show that the repeated indicator approach with (formative) measurement Mode B for the repeated indicators is generally preferable to model reflective-formative type hierarchical latent variable models.

Moreover, the empirical application demonstrates how reflective-formative type hierarchical latent variables can be used to model a strategically important process for a company, specifically, strategic human resource management activities which have been identified as a key component in realizing competitive advantage (Grundy, 1997) and have been linked to organizational performance (Maltz et al., 2003). Corporate reputation on a more general level represents a concept which

[2] We would like to thank an anonymous reviewer for this suggestion.

has been intensively studied in the strategic management literature (Rindova et al., 2010; Rindova et al., 2005). It represents an intangible asset for a company (Barney, 1991) and, as such, has been termed "*one of its [the organization's] most important strategic resources*" (Flanagan and O'Shaugnessy, 2005, p. 445). Corporate reputation may thus be viewed as a unique combination of internal investments, i.e., strategic management outcomes, and external evaluations which is difficult to imitate and may result in a competitive advantage, and ultimately, superior performance following the logic of the resource-based view (Barney, 1991; Boyd et al., 2010; Roberts and Dowling, 2002).

A strong and positive corporate reputation (as an employer) can be important in strategic human resource management as it facilitates the attraction of high-potential applicants, and may increase morale and productivity (Gray and Balmer, 1998; Schwaiger et al., 2010). Building an image or a reputation as an employer or, more specifically, building an employer brand is therefore "*a targeted, long-term strategy to manage the awareness and perceptions of employees, potential employees, and related stakeholders with regards to a particular firm*" (Sullivan, 2004, p. 1). Thus, understanding how a company's employer (brand) image is perceived and how managers can influence its perception to make the company more attractive for future employees, is crucial. The empirical application used in this paper hence contributes to the strategic management literature.

Hierarchical latent variable models using PLS-SEM

Conceptual background for hierarchical latent variable models

Hierarchical latent variable models, hierarchical component models, or higher-order constructs, are explicit representations of multidimensional constructs that exist at a higher level of abstraction and are related to other constructs at a similar level of abstraction completely mediating the influence from or to their underlying dimensions (Chin, 1998b). Law et al. (1998, p. 741) define "*[...] a construct as multidimensional when it consists of a number of interrelated attributes or dimensions and exists in multidimensional domains. In contrast to a set of interrelated unidimensional constructs, the dimensions of a multidimensional construct can be conceptualized under an overall abstraction, and it is theoretically meaningful and parsimonious to use this overall abstraction as a representation of the dimensions.*" As such, multidimensional constructs can be distinguished from unidimensional constructs which are characterized by a single underlying dimension (Netemeyer et al., 2003).

A theoretical concept is not *per se* characterized as a multidimensional or unidimensional construct but can usually be operationalized in either way, representing different levels of theoretical abstraction (Law et al., 1998). Job satisfaction which is a well and widely researched construct in management research may serve as an example to explain this notion (Law et al., 1998). Job satisfaction can be operationalized as a unidimensional construct consisting of a set of interrelated items measuring the overall job satisfaction level of employees. Several of these facet free scales exist in the literature (e.g., Brayfield and Rothe, 1951; Quinn and Staines, 1979) and are also used in the strategic management literature (e.g., Birnbaum and Somers, 1993; Law and Wong, 1999). In contrast, other studies use a multidimensional measurement instrument (e.g., Chacko, 1983; Law et al., 1998), in which job satisfaction consists of five distinct dimensions: satisfaction with (1) pay, (2) supervisor, (3) co-workers, (4) promotion and (5) the work itself.

Typically, hierarchical latent variable models are characterized by (1) the number of levels in the model (often restricted to second-order models) (Rindskopf and Rose, 1988) and (2) the relationships (formative vs. reflective) between the constructs in the model (Edwards, 2001; Jarvis et al., 2003; Ringle et al., 2012; Wetzels et al., 2009).

In general, a higher (or second)-order construct is a general concept that is either represented (reflective) or constituted (formative) by its dimensions (lower (or first)-order constructs). Therefore, the relation between the higher and lower-order constructs is not a question of causality, but rather a question of the nature of the hierarchical latent variable, as the higher-order construct (the general concept) does not exist without its lower-order constructs (dimensions). If the higher-order construct is reflective, the general concept is manifested by several specific dimensions themselves being latent (unobserved). If the higher-order construct is formative, it is a combination of several specific (latent) dimensions into a general concept (Edwards, 2001; Wetzels et al., 2009).

There is no agreement on the terminology for hierarchical latent variable models (Wetzels et al., 2009), but on the basis of a second-order hierarchical latent variable model, Ringle et al. (2012) and Jarvis et al. (2003) distinguish four types of models contingent on the relationship among (1) the first-order latent variables and their manifest variables, and (2) the second-order latent variable(s) and the first-order latent variables (Figure 1).

First, in the **reflective-reflective type I model**, the lower-order constructs are reflectively measured constructs themselves that can be distinguished from each other but are correlated. Lohmöller (1989) calls this type of model 'hierarchical common factor model', where the higher-order construct represents the common factor of several specific factors. Therefore, this type of hierarchical latent variable model is most appropriate if the objective of the study is to find the common factor of several related, yet distinct reflective constructs. However, Lee and Cadogan (in press) argue that there is "*no such thing*" as a reflective-reflective hierarchical latent variable model and that such a model is "*at worst, misleading, and at best meaningless*" (Lee and Cadogan, in press, p. 3). Reflective measures should be unidimensional and conceptually interchangeable which conflicts with the view of multiple underlying dimensions being distinct in

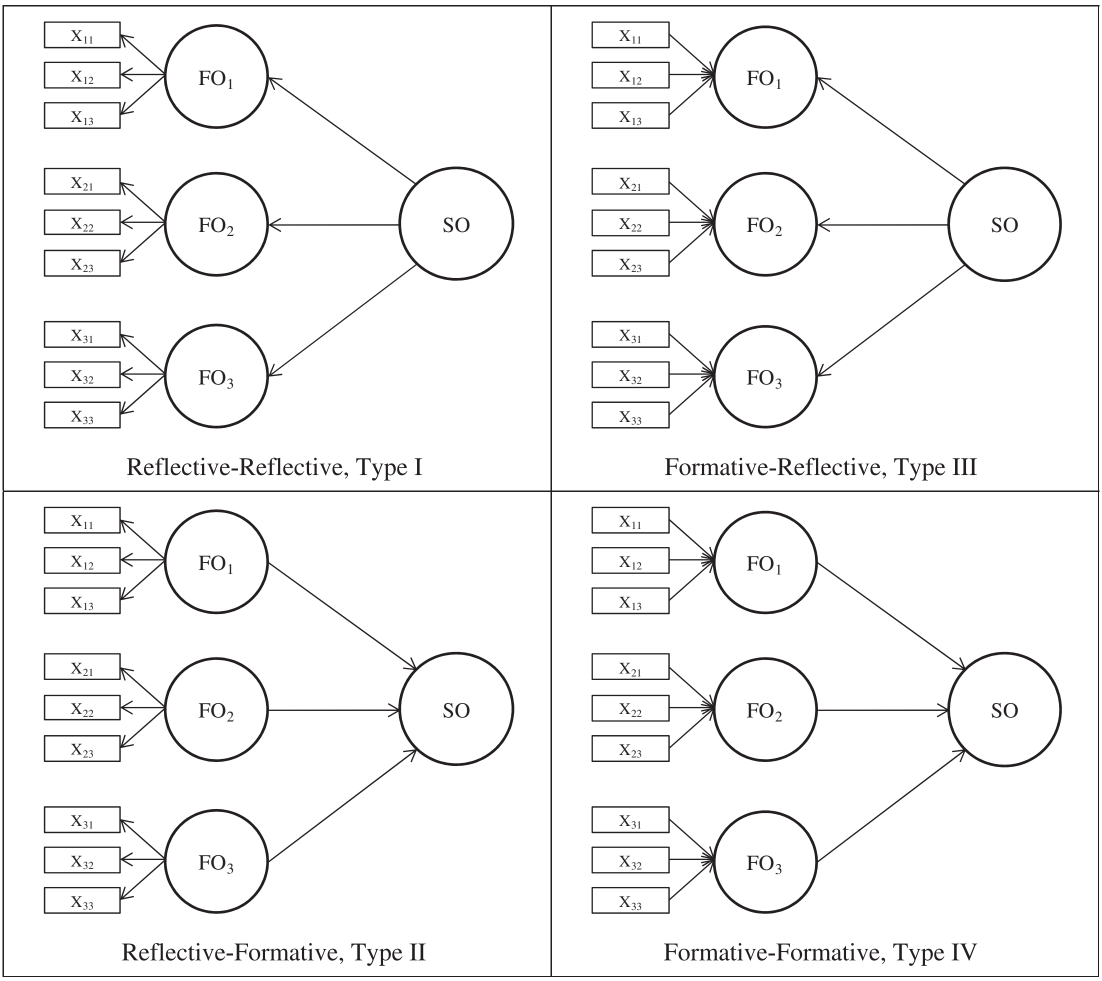

Figure 1. The four types of hierarchical latent variable models

nature. Thus, it is either unnecessary to model the lower-order constructs as separate constructs because they should be identical according to a reflective logic or, if multiple distinct dimensions indeed exist, these dimensions should be modeled as formative, leading to a reflective-formative type hierarchical latent variable model (Lee and Cadogan, in press). An empirical example in the literature is the 'complementarity' construct of different types of knowledge relatedness (Tanriverdi and Venkatraman, 2005) consisting of five reflective constructs: (1) internal product knowledge relatedness, (2) external product knowledge relatedness, (3) customer knowledge relatedness, (4) risk & investment knowledge relatedness, and (5) alliance management knowledge relatedness which are reflectively related to the overarching complementarity construct. Yet, this construct exactly reflects the criticism by Lee and Cadogan (in press) as the five dimensions are distinct in nature and thus not interchangeable. This construct would probably be better represented in a reflective-formative type model.

Second, in the **formative-reflective type III model**, the higher-order construct is a common concept of several specific formative lower-order constructs. Examples in the empirical literature are rather scarce, but a meaningful application of such a model could be firm performance as a reflective higher-order construct measured by several different indices of firm performance as formative lower-order constructs. Firm performance represents one of the most important constructs in strategic management (e.g., Venkatraman and Ramanunjam, 1986). Performance indices that combine different performance-relevant characteristics are well represented by formative constructs (Jarvis et al., 2003; Petter et al., 2007). The objective of such a higher-order performance construct would be to represent the common part of several indices that claim to measure the same thing (firm performance) yet using different techniques to accomplish this task. This approach helps to overcome the weaknesses (missing areas) of each single index.

Third, in the **reflective-formative type II model**, the lower-order constructs are reflectively measured constructs that do not share a common cause but rather form a general concept that fully mediates the influence on subsequent endogenous variables (Chin, 1998b). An empirical example could be the multidimensional 'STROBE' construct (Strategic Orientation of Business Enterprises) which consists of the reflectively measured first-order constructs riskiness, proactiveness, futurity, defensiveness, analysis and aggressiveness (Venkatraman, 1989), although it was not explicitly operationalized as formative higher-order construct. Another example is the instrumental and symbolic dimension of an employer brand image, as we will illustrate in our empirical application. Sometimes, these types of hierarchical latent variables are also used to account for the measurement error of the indicators of a "normal" formative construct: the indicators are operationalized as reflective constructs to explicitly model their measurement error (Cadogan and Lee, in press; Edwards, 2001).

Fourth, in the **formative-formative type IV model**, the lower-order constructs are formatively measured constructs that form a more abstract general concept. This is often done if several management-relevant concepts are subsumed under the general concept. An example of such a model could also be firm performance as higher-order construct. However, in contrast to the formative-reflective type model, a formative-formative type model would not comprise different indices of overall firm performance but different aspects of performance such as the performance of different organizational activities or subdivisions (e.g., R&D performance, HR performance, sales performance, etc.) that determine the overall firm performance (Jarvis et al., 2003; Petter et al., 2007). Moreover, the formative-formative type model can also be useful to structure a complex formative construct with many indicators into several sub-constructs.

Although some hierarchical latent variable model types are less likely to be used, all of these types can be found in empirical research. Ringle et al. (2012) report that out of 109 empirical studies in the information systems flagship journal *MIS Quarterly* using PLS-SEM, 15 studies (23.08%) reported 25 hierarchical latent variable models. Of these 25 models, the reflective-formative type (13 models (52%)) and formative-formative type (6 models (24%)) were most frequently employed. This indicates the predominance of formative type hierarchical latent variable models, even though clear guidelines on their usage are missing in the literature.

In addition, in most studies (13 studies (86.67%)) the higher-order latent variable was embedded in a nomological network of latent variables serving as antecedent (5 studies (33.33%)), consequent (3 studies (20%)) or both (5 studies (33.33%)) (Ringle et al., 2012). Therefore, it is necessary not to limit the discussion to hierarchical latent variable models as separate constructs, but to also consider their potential application in a nomological network of latent variables.

Estimation of hierarchical latent variable models in PLS-SEM

PLS-SEM requires the computation of construct scores for each latent variable in the path model. As observed variables (or indicators) to estimate the construct scores of a higher-order construct do not exist, three approaches to model hierarchical latent variables in PLS-SEM have been proposed in the literature: (1) the repeated indicator approach (Lohmöller, 1989; Wold, 1982), (2) the sequential latent variable score method or two-stage approach (Ringle et al., 2012; Wetzels et al., 2009), and (3) the hybrid approach (Wilson and Henseler, 2007).

For the repeated indicator approach, a higher-order latent variable can be constructed by specifying a latent variable that represents all the manifest variables of the underlying lower-order latent variables (Lohmöller, 1989; Noonan and Wold, 1983; Wold, 1982). For example, if a second-order latent variable consists of three underlying first-order latent variables, each with four manifest variables, the second-order latent variables can be specified using all (twelve) manifest variables of the underlying first-order latent variables. Consequently, the manifest variables are used twice: (1) for the first-order latent variable ("primary" loadings/weights) and (2) for the second-order latent variable ("secondary" loadings/weights). Having specified the outer model (measurement model) in this way, the inner model (structural model) accounts for the hierarchical component of the model, as the path coefficients between the first-order and second-order constructs represent the loadings/weights of the second-order latent variable. Obviously, this approach can easily be extended to higher-order hierarchical models (e.g., Noonan and Wold, 1983; Wetzels et al., 2009).

The sequential latent variable score method, or two-stage approach, has the advantage that latent variable scores are determined in PLS-SEM, and thus latent variables scores for lower-order latent variables can be obtained (Chin, 1998a; Lohmöller, 1989; Tenenhaus et al., 2005). It estimates the construct scores of the first-order constructs in a first-stage model without the second-order construct present, and subsequently uses these first-stage construct scores as indicators for the higher-order latent variable in a separate second-stage analysis (e.g., Agarwal and Karahanna, 2000; Wetzels et al., 2009; Wilson and Henseler, 2007). However, one can also estimate a repeated indicator model in the first-stage and then use the first-order construct scores in a separate second-stage (Ringle et al., 2012; Wilson, 2010).

The hybrid approach works similar to the repeated indicator approach but uses each indicator (manifest variables) only once in a model to avoid artificially correlated residuals. It splits the indicators of each first-order construct and uses one half to estimate the first-order construct and the other half to estimate the second-order construct, therefore avoiding the repeated use of indicators in the model (Wilson and Henseler, 2007).

The advantage of the repeated indicator approach is its ability to estimate all constructs simultaneously instead of estimating lower-order and higher-order dimensions separately. Thus, it takes the whole nomological network, not only the lower level or the higher level model into account, thereby avoiding interpretational confounding. When using the repeated indicator approach, researchers have to make decisions regarding the mode of measurement for the higher-order construct and the inner weighting scheme. First, as for any construct in a PLS-SEM model, the mode of measurement for the higher-order repeated indicators needs to be specified (i.e., Mode A or Mode B). Usually, Mode A measurement is associated with reflective constructs and Mode B is associated with formative constructs (Henseler et al., 2009; Tenenhaus et al., 2005). The standard approach for repeated indicators on a hierarchical latent variable is to use Mode A (Wold, 1982) which generally suits reflective-reflective type models best. Therefore, formative type models are often also estimated using Mode A for the repeated indicators, especially when the first-order constructs are reflective (i.e., reflective-formative type) (Chin, 2010; Ringle et al., 2012), although the formative nature of the higher-order construct might suggest Mode B measurement. Therefore, we think it is more appropriate to use Mode B for the repeated indicators of a formative type hierarchical latent variable model (i.e., reflective-formative and formative-formative types). However, the importance of the mode of measurement is usually not discussed in research papers presenting the repeated indicator approach, but only indirectly inferred by the direction of arrows in the path diagram (Chin, 2010; Ringle et al., 2012).

Second, besides the mode of measurement, Lohmöller (1989) analytically discusses how setting the inner weighting scheme (factor or path weighting) together with the mode (Mode A or Mode B) leads to different (or equal) results for the different types of hierarchical latent variables. Thus, researchers have to be aware that the type of inner weighting scheme they choose can make an important difference in the results of a repeated indicator model. However, Lohmöller (1989) does not provide guidelines on which setting is more suitable for each type.

In addition, it is frequently mentioned that the repeated indicator approach is only advisable if the lower-order constructs have an equal number of indicators, otherwise leading to biased loadings/weights for the lower-order construct on the higher-order constructs (Chin et al., 2003; Lohmöller, 1989; Ringle et al., 2012). However, to the best of our knowledge, an assessment of this general assumption is missing in the literature.

A disadvantage of the repeated indicator approach is the repeated use of the same indicators that can cause artificially correlated residuals. The hybrid approach avoids this disadvantage by randomly splitting the indicators and using them only once: on the first-order construct or on the second-order construct. A clear disadvantage of this approach is the reduced reliability of the measures having only half the number of indicators. This could especially be a problem as PLS-SEM is known to be 'consistent at large', meaning that estimates are consistent if sample size and number of indicators increase (Lohmöller, 1989). Using the hybrid approach, there are no clear guidelines on whether Mode A or Mode B should be used for the formative second-order construct.

When using the two-stage approach, one usually uses the mode of measurement for the higher-order construct in the second stage that matches the construct's operationalization, i.e., Mode B for a formative and Mode A for a reflective construct. The two-stage approach has the advantage of estimating a more parsimonious model on the higher level analysis without needing the lower-order constructs. On the downside, the separate estimation of the lower and higher-order level models might cause interpretational confounding because it does not take the whole nomological network into account (Wilson and Henseler, 2007).

Another important difference between the approaches emerges when hierarchical latent variables are used in a nomological network of latent variables as an endogenous construct (i.e., a consequence or criterion). When the repeated indicator approach is used, regardless of Mode A or Mode B measurement, and the higher-order construct is formative (i.e., reflective-formative or formative-formative), the lower-order constructs already explain all the variance of the higher-order construct (i.e., R^2 equals 1.0). Therefore, other antecedent constructs cannot explain any variance of the higher order-construct and consequently, their paths to the higher-order construct will be zero (nonsignificant) (Ringle et al., 2012; Wetzels et al., 2009). This problem does not occur when the two-stage approach is used for formative hierarchical constructs (Ringle et al., 2012). Therefore, Ringle et al. (2012) suggest using the two-stage approach whenever the PLS-SEM model involves a formative hierarchical latent variable model in an endogenous position.[3]

However, we question the use of the two-stage approach for formative hierarchical latent variables as recommended by Ringle et al. (2012) as the only possibility to assess the effect of antecedent constructs on a higher-order construct and alternatively propose the application of the repeated

[3] The hybrid approach is similar to the repeated indicator approach. Ideally, when the indicators have a high reliability, the formative second-order construct should also be completely explained by its first-order constructs. Due to measurement error, this will only rarely be the case in empirical research. Nevertheless, the first-order constructs already explain most of the variance in the second-order construct, allowing only for marginal effects of antecedent constructs that would not resemble their true effects.

indicator or hybrid approach. Adapting an idea from Cadogan and Lee (in press), we propose to model the effect of antecedent constructs on formative higher-order constructs through its measures, hence its lower-order constructs. Modeling the effect through the lower-order constructs enables the researcher to assess the effect of antecedent constructs on the formative higher-order construct via the total effect (i.e., the sum of the effects on the lower-order constructs multiplied by the effect of the lower-order constructs on the higher-order construct). This method has the advantage that it is conceptually superior to the two-stage approach, as antecedents are conceptually supposed to have an effect on the formative indicators of a construct (Cadogan and Lee, in press). Therefore, it is possible to estimate the direct effects of the antecedents on the lower-order constructs.

Another option would be an additional step of analysis that regresses the antecedent construct scores on the higher-order construct scores. This option yields exactly the same results as the total effect because the second-order construct is fully explained by the mediating first-order constructs, but it has the disadvantage of needing a further step of analysis.

Simulation study

We use simulations with artificial data for which we know a priori the true path coefficients to assess the performance of the three modeling approaches to specify reflective-formative hierarchical latent variable models in PLS-SEM. Based on the results of the simulations, we provide guidelines on which method is preferable in an empirical setting where the true parameters are unknown.

The conceptual model for our simulations is a model with one exogenous latent variable having four reflective indicators, one second-order hierarchical latent variable model with three first-order constructs that form the second-order construct (reflective first-order − formative second-order), and one final endogenous latent variable with four reflective indicators. The exogenous construct has an effect on the second-order construct and the second-order construct influences the final endogenous construct (Figure 2). Hence, the hierarchical latent variable is part of a greater nomological network and serves both as antecedent and consequent. Simulations on cause-effect relationship models require the generation of data for indicator variables that meet (after estimation of the model) the pre-specified (true) parameters of relationships in the structural model as

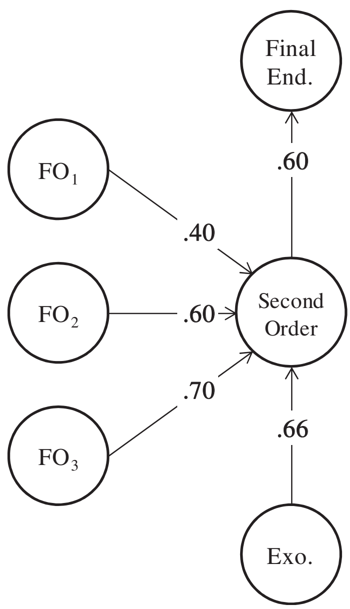

Figure 2. Conceptual model of the simulation study

well as in the measurement models. For SEM models, there are two different approaches suited for obtaining such data: The first approach calculates the implied covariance matrix of the indicators for given values of the parameters in the model and generates data from a multivariate distribution that fits this covariance matrix. The second approach first generates construct scores of the latent variables that match the (true) specified relations in the structural model (i.e., path coefficients) and then generates data for the observed variables (indicators) by adding measurement errors to match the indicators' true parameters in the measurement model (i.e., outer loadings). Most simulation studies that assess PLS-SEM models use the second data generation approach that better matches the properties of the PLS-SEM method (e.g., Chin et al., 2003; Henseler and Chin, 2010; Reinartz et al., 2009).

Therefore, we simulate data by (1) generating random multivariate normal variables for the latent variable scores starting with the exogenous latent variables, (2) adding structural relation errors that match the true relationships in the structural model (path coefficients), and (3) compute the indicators (manifest variables) by adding measurement errors to match the indicators' true parameters (loadings) in the measurement model.

For the path coefficients, we set the relation between the exogenous and second-order construct to .66, the first-order weights to .40, .60 and .70 and the relation to the final endogenous variable to .60 (Figure 2).[4] We then vary three different factors: (1) the *sample sizes* (i.e., 50, 100 and 500), (2) the reliability of the reflective measures (i.e., *loadings* of .70, .80, and .90), and (3) whether the first-order constructs have equal *numbers of indicators* (i.e., all have four indicators) or unequal numbers of indicators (two constructs have four indicators and one has eight indicators). We generate 1,000 datasets per condition in Gauss 8.0 and estimate each approach with the three different *inner weighting schemes* (i.e., centroid, factor and path weighting). This results in $3 \times 3 \times 3 \times 2 \times 1000 = 54{,}000$ computations per approach.

We estimate five different models with the SmartPLS 2.0 software (Ringle et al., 2005). In the first two models, we specify the second-order construct with the repeated indicator approach, using either Mode A or Mode B for the repeated indicators on the second-order construct. In the second two models, we use the hybrid approach with either Mode A or Mode B for the indicators on the second-order construct. To estimate the effect of the exogenous latent variable on the higher-order dimension, we estimate the total effect through the first-order constructs (Figures B.1 and B.2 in Appendix B) as proposed earlier. In the fifth model, we use the two-stage approach estimating a first-level model with only the first-order constructs and the endogenous and exogenous variable in the first stage, and then use the latent variable scores of the first-order constructs as formative indicators (Mode B) of the second-order construct in a second stage.[5] This formative second-order construct is directly influenced by the exogenous construct and affects the final endogenous variable (Figure B.3 in Appendix B).

We assess all five approaches by comparing the known true parameters (i.e., the path coefficients and formative outer weights) with the estimated values. For each approach, the smaller the differences between the true values and the parameter estimates, the better the parameter recovery. Consistent with prior studies (e.g., Henseler and Chin, 2010; Reinartz et al., 2009), we evaluate parameter recovery using the mean absolute relative bias (MARB), that is, the average of the simple absolute deviations between the true parameter and the estimated parameter divided by the true parameter and the root mean squared error (RMSE). We calculated the parameter recovery for all relevant parameters in total (incoming path, outgoing path, and weights from the first to the second-order construct) and separately.[6] In addition, we assessed the reliability of the second-order

[4] The complete population model for the simulation can be found in Appendix A.

[5] We also use different first-stage models, namely, the repeated indicator Mode A and Mode B model and a simple principal components extraction of the first-order construct. All four models yield nearly identical results (nonsubstantial differences).

[6] As both RMSE and MARB yield equivalent conclusions (i.e., their correlations exceed 0.9), we only report results for RMSE. The complete MARB results are available from the authors upon request.

Table 1. Reliability of the estimated second-order construct scores (squared correlation) for each approach

Factors		Repeated indicators Mode B	Repeated indicators Mode A	Hybrid Mode B	Hybrid Mode A	Two-stage
Loadings	.70	.818	.797	.715	.703	.796
	.80	.878	.855	.816	.789	.854
	.90	.926	.900	.895	.867	.898
Sample size	50	.870	.849	.805	.783	.846
	100	.876	.851	.808	.785	.850
	500	.877	.852	.813	.791	.851
Number of indicators	Equal	.864	.850	.788	.778	.839
	Unequal	.884	.852	.829	.795	.860
Weighting scheme	Centroid	.874	.883	.811	.812	.850
	Factor	.845	.855	.794	.793	.849
	Path	**.903**	.814	.821	.755	.849
Overall		.874	.851	.809	.787	.849

Note: The best results between approaches are highlighted in bold and underlined.

constructs by calculating the squared correlation between the true second-order score from our simulation and the estimated latent variable score of the second-order construct for each approach.[7]

Tables 1–5 present the mean simulation results for each approach with different parameter recovery measures (squared correlation, RMSE total, RMSE incoming path, RMSE outgoing path, and RMSE weights) for each factor.

Table 1 shows that the repeated indicator approach with Mode B (RI-B) on the second-order construct and inner path weighting scheme provides the most reliable second-order construct score in terms of the squared correlation between the true and the estimated scores with .903. The reliability of the construct scores for all approaches, except the two-stage approach, is significantly and substantially[8] influenced by the weighting scheme: e.g., using the factor or centroid weighting scheme provides significantly lower squared correlations for the RI-B. (See MANOVA results for all performance measures and all approaches in Appendix C). The hybrid approach (both with Mode A and B, regardless of the inner weighting scheme) provides the worst results. Of all the tested approaches, the factor weighting scheme provides the worst results.

All approaches are substantially influenced by the reliability of the reflective measures, but not by the sample size. Moreover, the squared correlation for all approaches (except for repeated indicators Mode A (RI-A)) are influenced when the number of indicators is unequal, increasing the reliability of the second-order construct scores. This effect is most probably due to the increased reliability of the measurement instrument having four additional indicators in the unequal indicators condition than in the equal indicators condition. The increased reliability effect is further supported by a substantial interaction between loadings and the equal/unequal indicators condition for all approaches, indicating that with lower loadings, the increased number of indicators in the unequal indicators condition provides more reliable construct scores.

Table 2 shows that the RI-B with an inner path weighting scheme also provides the overall best parameter recovery (RMSE of .091). The second best approach is the RI-A with a centroid weighting scheme, followed by the two-stage approach regardless of the weighting scheme.

The RI-B with a path weighting scheme is especially good at recovering the path from the second-order construct to the endogenous variable (high predictive validity; Table 4) and the weights of the first-order constructs on the second-order construct (high construct validity; Table 5). The two-

[7] We would like to thank an anonymous reviewer for this suggestion.

[8] We define a substantial effect as being significant and explaining more than 5% of the total variance in the dependent variable, implying a partial η^2 of more than .05 (Reinartz et al., 2009). This condition is necessary because even very small effects become significant due to very large sample sizes in MANOVA (i.e., 54,000 observations per approach).

Table 2. Results for parameter recovery (RMSE) of all relevant parameters in the model (RMSE Total) for each approach

Factors		Repeated indicators Mode B	Repeated indicators Mode A	Hybrid Mode B	Hybrid Mode A	Two-stage
Loadings	.70	.130	.163	.221	.234	.149
	.80	.117	.150	.170	.198	.141
	.90	.111	.143	.134	.165	.140
Sample size	50	.125	.155	.181	.204	.147
	100	.117	.151	.176	.200	.142
	500	.115	.149	.169	.194	.141
Number of indicators	Equal	.120	.139	.183	.191	.147
	Unequal	.118	.165	.167	.208	.140
Weighting scheme	Centroid	.119	.118	.169	.178	.142
	Factor	.146	.151	.181	.195	.144
	Path	**<u>.091</u>**	.186	.176	.224	.144
Overall		.119	.152	.175	.199	.143

Note: The best results between approaches are highlighted in bold and underlined.

stage approach is best in recovering the incoming relation, that is, the path from the exogenous construct to the second-order construct (Table 3). Interestingly, the RI-B with a factor weighting scheme is equally good at recovering the incoming relation, but produces biased estimates for the weights and outgoing relation. Examining the parameter estimates of the various approaches (Table D.1 in Appendix D), it becomes apparent that the RI-B with factor weighting provides virtually the same results as the two-stage approach. Both approaches underestimate the weight of the most important first-order construct (FO_3) and overestimate the weight of the second most important first-order construct (FO_2). It may be that these approaches capitalize on a strong correlation between FO_2 and the exogenous construct (.60) which is higher than the correlation to the other two constructs (.40 and .20). Yet, this reveals a shortcoming of these two approaches.

Having unequal numbers of indicators does not substantially influence the parameter recovery for the RI-B and the two-stage approach regardless of the weighting scheme. In contrast, the

Table 3. Results for parameter recovery (RMSE) of the path from the exogenous to the second-order construct (RMSE incoming path) for each approach

Factors		Repeated indicators Mode B	Repeated indicators Mode A	Hybrid Mode B	Hybrid Mode A	Two-stage
Loadings	.70	.158	.203	.203	.232	.136
	.80	.111	.161	.141	.182	.088
	.90	.074	.128	.089	.138	.050
Sample size	50	.116	.166	.147	.186	.094
	100	.113	.164	.144	.184	.090
	500	.113	.163	.142	.182	.090
Number of indicators	Equal	.114	.105	.133	.128	.091
	Unequal	.114	.224	.156	.241	.091
Weighting scheme	Centroid	.106	.134	.131	.157	**<u>.091</u>**
	Factor	**<u>.092</u>**	.151	.125	.173	**<u>.091</u>**
	Path	.145	.208	.178	.223	**<u>.092</u>**
Overall		.114	.164	.145	.184	.091

Note: The best results between approaches are highlighted in bold and underlined.

Table 4. Results for parameter recovery (RMSE) of the path from the second-order to the final endogenous construct (RMSE outgoing path) for each approach

Factors		Repeated indicators Mode B	Repeated indicators Mode A	Hybrid Mode B	Hybrid Mode A	Two-stage
Loadings	.70	.075	.084	.110	.115	.083
	.80	.037	.045	.054	.064	.044
	.90	.025	.028	.025	.030	.024
Sample size	50	.054	.061	.071	.078	.059
	100	.044	.050	.062	.068	.049
	500	.039	.045	.056	.063	.043
Number of indicators	Equal	.048	.051	.069	.071	.053
	Unequal	.043	.053	.057	.068	.048
Weighting scheme	Centroid	.045	.045	.062	.063	.050
	Factor	.051	.050	.066	.067	.051
	Path	**.041**	.061	.061	.078	.050
Overall		.046	.052	.063	.070	.050

Note: The best results between approaches are highlighted in bold and underlined.

parameter recovery of the RI-A and the hybrid approaches are substantially negatively influenced when first-order constructs have unequal numbers of indicators. Furthermore, these approaches show a substantial interaction with the weighting scheme. In particular, the path and the factor weighting scheme produce more biased results for these approaches. For the RI-A, it is interesting to note that (1) when the number of indicators is equal, the approach tends to result in all of the weights of the first-order construct being almost equal, i.e. having the same weight (e.g., tendency towards a weight of .5) and does not estimate different weights, and (2) when the number of indicators is unequal, the RI-A approach tends to overestimate the weight of the construct having the larger number of indicators than the other constructs (see Appendix D). Thus, the weights of the RI-A are biased regardless of having equal or unequal numbers of indicators and should be avoided for reflective-formative type hierarchical latent variables. Moreover, although the centroid weighting scheme for the RI-A in general (squared correlation and overall parameter

Table 5. Results for parameter recovery (RMSE) of the weights from the first-order to the second-order construct (RMSE weights) for each approach

Factors		Repeated indicators Mode B	Repeated indicators Mode A	Hybrid Mode B	Hybrid Mode A	Two-stage
Loadings	.70	.126	.162	.250	.260	.166
	.80	.128	.162	.199	.226	.171
	.90	.130	.163	.162	.192	.176
Sample size	50	.135	.164	.209	.230	.173
	100	.126	.162	.204	.228	.170
	500	.123	.161	.197	.221	.170
Number of indicators	Equal	.129	.161	.217	.228	.175
	Unequal	.126	.163	.190	.224	.167
Weighting scheme	Centroid	.135	.121	.199	.203	.170
	Factor	.175	.164	.216	.223	.172
	Path	**.074**	.201	.196	.251	.171
Overall		.128	.162	.204	.226	.171

Note: The best results between approaches are highlighted in bold and underlined.

recovery) appears to produce good results, this may be the outcome of the upward bias in the unequal indicators condition that brings the third weight (FO_3) closer to the true value compared to the equal indicators condition, while the factor and path weighting schemes heavily overestimate this particular weight und underestimate the other weights.

Generally, the incoming and outgoing relations are influenced by the reliability of the measures. It is known that PLS-SEM overestimates the loadings and underestimates the path coefficients (Lohmöller, 1989; Reinartz et al., 2009). However, the weights from the first-order to the second-order construct are not influenced by the reliability of the measures, except for the hybrid approaches. Thus, the construct validity of the formative second-order construct with the repeated indicator and two-stage approach is not influenced by the reliability of the first-order measures.

Overall, the results show that the repeated indicator approach with Mode B and path weighting scheme produces the best parameter estimates in terms of RMSE and MARB. The two-stage approach is the second best alternative. It produces less reliable second-order construct scores and more biased parameter estimates (expect for the incoming relation from the exogenous variable). The worst performers are the repeated indicator approach with Mode A and the hybrid approaches for this type of hierarchical latent variable. In particular, the repeated indicator approach with Mode A is strongly affected when the lower-order constructs have unequal numbers of indicators.

Empirical application

Context and conceptual framework

The resource-based view (RBV) argues that heterogeneously distributed resources may result in a sustainable competitive advantage (SCA) if they satisfy the "VRIN" conditions (valuable, rare, inimitable, non-substitutable) (Barney, 1991). Corporate reputation thus represents an important strategic resource because a unique corporate reputation (or a corporate image) may constitute a competitive advantage, leading to superior company performance (Grant, 1991; Roberts and Dowling, 2002). Corporate reputation may not only refer to the overall extent to which an organization is highly regarded compared with its competitors (Weiss et al., 1999), but it is also a major determinant in recruiting new talent (Belt and Paolillo, 1982). A qualified human resources pool has been identified as critical for a company's (long term) sustainable development (Kim et al., 2011), while Wright and McMahan (1992) argue that a firm's human resources provide a potential source of SCA within the RBV. Consequently, corporate reputation can act as a "brand" (Cable and Turban, 2003), signaling "*the package of functional, economic, and psychological benefits […] identified with the employing company*" (Ambler and Barrow, 1996, p. 187) to "*[...] employees, potential employees, and related stakeholders with regards to a particular firm*" (Backhaus and Tikoo, 2004, p. 501; Sullivan, 2004). In this sense, corporate reputation can also be defined as employer brand.

Leveraging a company's (employer) brand may be a critical success factor in winning potential future employees (e.g., Ambler and Barrow, 1996) which ultimately determines a company's long-term success. Hence, understanding how a company's employer brand image is perceived, and how managers can influence its perception to make the company more attractive for future employees, is one of the most relevant strategic and long-term decisions in the context of human resources management.

We use the so-called "symbolic-instrumental framework" taken from the human resources literature to illustrate the use of formative hierarchical latent variables in a strategic management context, and show how PLS-SEM can be used to estimate the effect of antecedent constructs on formative higher-order constructs through its lower-order constructs. We model two hierarchical latent variables, the symbolic dimension and the instrumental dimension of an employer brand image, and relate the two second-order constructs to employer attractiveness to illustrate how ignoring the indirect effect of the symbolic dimension on the instrumental dimension leads to biased results.

The “instrumental-symbolic framework” (Lievens and Highhouse, 2003) is related to Keller’s brand equity framework (1993). With regard to an employer brand image, Keller’s product-related associations that describe “functional” or instrumental benefits of a product might encompass objective and factual elements of employment with a company, e.g., salary, career opportunities, etc. (Backhaus and Tikoo, 2004). On the other hand, in the context of employer branding, the non-product related attributes or associations refer to inferences consumers make about a specific brand, e.g., brand (company) personality attributes (Keller, 1993) and thus reflect the more abstract perceptions people have about a specific company.

The employer brand can be seen as a company resource within the RBV that may be decomposed into combinations of factors that will lead to a SCA. Different configurations of these resource factors may allow different competitive strategies to achieve an equal level of SCA (Black and Boal, 1994). Thus, the two dimensions of an employer brand as well as the underlying sub-dimensions may adequately represent the underlying relationships in a configural model of factor resources within the RBV. In addition, following the guidelines developed by Jarvis et al. (2003), the application of a formative approach may best represent such a model because several factor combinations can lead to the same overall outcome.

Previous literature has linked various instrumental and symbolic factors to the attractiveness of a company as an employer (e.g., Lievens and Highhouse, 2003; Slaughter and Greguras, 2009). These authors primarily modeled these factors as reflective constructs and then regressed attractiveness perceptions on them, i.e., they did not explicitly model the instrumental (ID) and the symbolic dimension (SD). We however use PLS-SEM to illustrate how these two dimensions can be assessed as formative second-order hierarchical latent variables that combine the reflective factors from prior studies under a general concept. Representing the symbolic and instrumental dimensions as hierarchical latent variables, where the individual factors used in prior studies represent sub-dimensions (first-order constructs, i.e., distinctive theoretical constructs measured with reflective indicators) which form the two second-order dimensions,[9] better represents their level of abstraction conceptually. This modeling approach allows for more theoretical parsimony and reduced model complexity. Referring to our example, we would otherwise need to model the effects of twelve lower-order dimensions, and could not make conclusions about which dimension, on an abstract level, is more important for influencing a company’s attractiveness as an employer.

Thus, our approach gives managers an indication how to prioritize employer branding activities and consequently structure their internal resources to achieve a sustainable competitive advantage. Most importantly however, modeling the symbolic and instrumental dimensions as hierarchical second-order constructs, allows us to assess the effect of the symbolic dimension on the instrumental dimension. This assessment is absent in prior literature on employer branding, but it is important from a theoretical perspective. Potential applicants to a company may not possess a sound pool of information about a specific company due to the difficulty of acquiring information on certain factors (e.g., a company’s culture or career opportunities) without actually working at the company. Consequently, they may use their general perceptions of the company as signals about working conditions (Rynes, 1991), i.e., they may use their more symbolic (personality) perceptions of a company to make inferences about the factual attributes of a specific job. Aaker (1997) suggests that brand personality perceptions may also bias other brand attributes. Therefore, the symbolic dimension may produce an indirect effect inasmuch as the symbolic dimension influences the perception of the instrumental dimension which, in turn, affects an employer’s attractiveness. An overview of the empirical application model is depicted in Figure 3.

Sample and method

We conducted a web-based survey among German students. The final sample consisted of 663 participants (58.7% were female). Seven well-known FMCG companies, actively doing business in Germany, were evaluated as employer brands. These companies held different positions in Universum

[9] This description corresponds to a reflective-formative type hierarchical latent variable model in our typology.

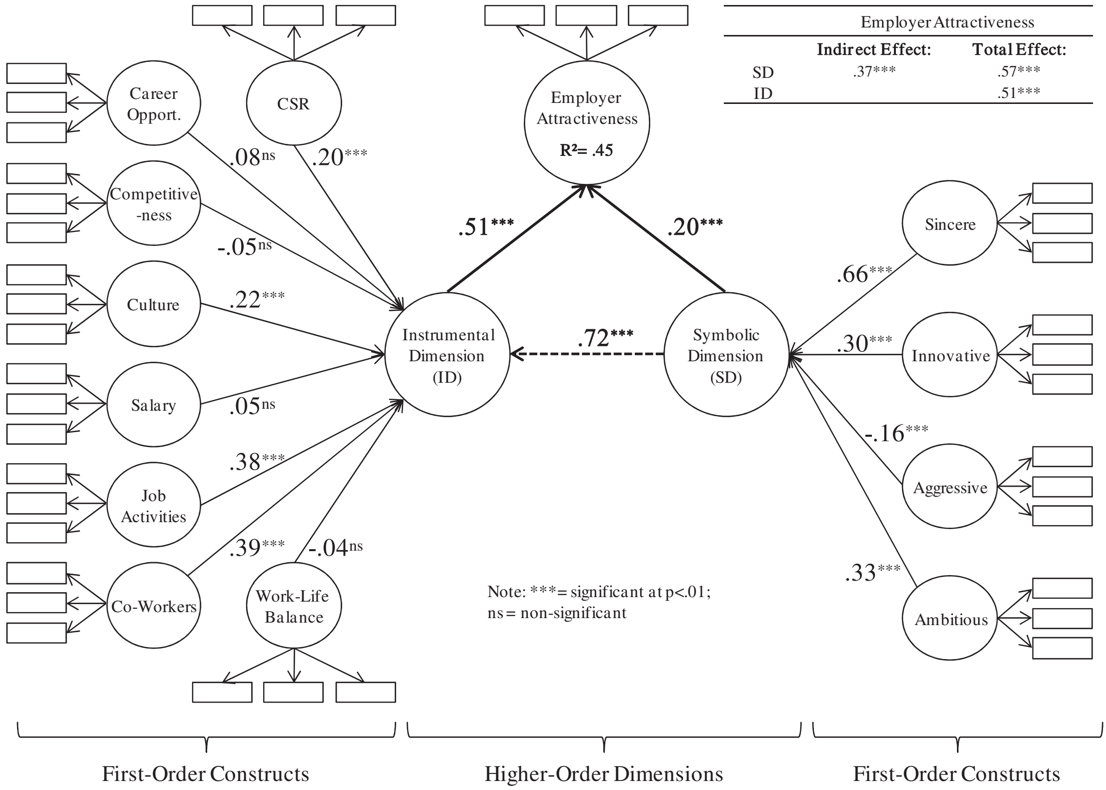

Figure 3. Conceptual model and PLS-SEM results for repeated indicator approach

Communications' "World's Most Attractive Employers" student ranking. The participants were each randomly assigned one questionnaire corresponding to one company.

Company attractiveness is the dependent variable and is modeled reflectively using 5 items (Table E.1 in Appendix E; Aiman-Smith et al., 2001).

We identified important instrumental factors from the literature, including career opportunities, work-life balance, salary, and company culture (e.g., Knox and Freeman, 2006; Tüzüner and Yüksel, 2009). To measure the SD facets, we used the items suggested by Davies et al. (2004) to assess a company's character (e.g., "honest", "exciting", or "arrogant"; Table E.2 in Appendix E). Exploratory and confirmatory factory analyses indicated the formation of 8 instrumental (with 30 indicators in total) and 4 symbolic facets (with 26 indicators in total). All these reflectively measured first-order facets of both the ID and the SD showed satisfactory values for convergent validity and reliability (i.e., AVE above .50 and composite reliability above .70) as well as discriminant validity following the Fornell—Larcker criterion[10] (Fornell and Larcker, 1981; Henseler et al., 2009).

We model the two higher-order dimensions (symbolic and instrumental) utilizing the two best alternatives resulting from our simulations, the repeated-indicator approach with Mode B and the two-stage approach, to illustrate the practical abilities of both approaches with this empirical application. For the repeated indicator approach, we use all first-order construct indicators also as indicators for the second-order construct (the symbolic and instrumental dimension) operationalized with Mode B on the second-order construct and the path weighting scheme. To assess the effect of the symbolic dimension on the instrumental dimension, we model the influence on the formative higher-order dimension through the first-order facets. Hence, we include paths from the symbolic dimension to each first-order construct of the instrumental dimension and assess the total effect of the symbolic dimension on the instrumental dimension through the first-order constructs as described previously.

[10] The complete results can be found in Table E.1, E.2, and E.3 in Appendix E.

For the two-stage approach, we estimate the model with the first-order constructs linked to the final endogenous variable attractiveness and save the latent variables scores of each first-order construct. We then use these latent variable scores as formative indicators (Mode B) for the second-order constructs.

Findings

We estimated the model using SmartPLS 2.0 (Ringle et al., 2005). Figure 3 shows the PLS-SEM path coefficient estimates from the repeated indicator model and their significance (applying a bootstrapping procedure with 1.000 replications (Henseler et al., 2009)). Table 6 compares the results of the path coefficients for the repeated indicator and two-stage approaches. Generally, both approaches yield similar results for most of the path coefficients, corresponding to our simulation example. In both approaches, we find significant direct effects of both the symbolic dimension (SD) and the instrumental dimension (ID) on attractiveness. We also examined the mediation of ID by assessing the indirect effect of SD on attractiveness using the bootstrap procedure in PLS-SEM (e.g., Preacher and Hayes, 2008; Shrout and Bolger, 2002). The indirect effect of SD via ID on attractiveness is significant and substantial.

The direct effects show that ID has a stronger effect (.51/.46) on attractiveness than SD (.20/.20). However, SD has a strong direct effect on ID as well (.72/.77). Taking the indirect effect of SD on attractiveness (.37/.36) into account by calculating the total effects reveals that SD may be as important (.57/.56) as ID (.51/.46). Consequently, models that do not account for this additional

Table 6. Comparison of the repeated indicator and two-stage approach

	Repeated indicator approach		**Two-stage approach**	
	Estimate	**P-Value**	**Estimate**	**P-Value**
Symbolic dimension (R^2 = .99)[a]				
Aggressive	−.16	.00	.17	.00
Ambitious	.33	.00	.27	.00
Innovative	.30	.00	.32	.00
Sincere	.66	.00	.68	.00
Instrumental dimension (R^2 = .99)[a]				
CSR	.20	.00	.24	.00
Career Opportunities	*.08*	*.17*	*−.01*	*.76*
Co-workers	.39	.00	.28	.00
Competitiveness	*−.05*	*.32*	.22	.00
Culture	.22	.00	.33	.00
Job Activities	.38	.00	.26	.00
Salary	*.05*	*.28*	*−.03*	*.46*
Work-Life Balance	*−.04*	*.29*	*−.01*	*.84*
Symbolic Dimension (R^2 = .53)	.72	.00	.77	.00
Employer attractiveness (R^2 = .45)				
Instrumental Dimension	.51	.00	.46	.00
Symbolic Dimension	.20	.00	.20	.00
Symbolic Dimension Indirect	.37	.00	.36	.00
Symbolic Dimension Total	.57	.00	.56	.00

Note: Nonsignificant effects are highlighted in italics.

[a] Typically the R^2 of a formative higher-order construct roughly equals 1 because it is fully explained by its facets.

indirect effect may substantially underestimate the importance of the symbolic dimension in explaining employer attractiveness.

Comparing the repeated indicator to the two-stage approach reveals diverging results. With the repeated indicator approach, all facets of the symbolic dimension have a significant influence on the higher-order dimension and hence on employer attractiveness. Moreover, all symbolic facets have a significant influence on the instrumental dimension.[11] Conversely, we find nonsignificant influences of the first-order, instrumental facets career opportunities, competitiveness, salary and work-life balance on the instrumental dimension and hence on employer attractiveness.

In contrast, the two-stage approach produces two different results within the first-order constructs: aggressiveness has a significant positive, rather than significant negative influence on the symbolic dimension, and competitiveness has a significant influence on the instrumental dimension. This comparison demonstrates that researchers should be aware that their PLS-SEM findings may change depending on the approach they choose.

The sign change of aggressiveness significantly alters the interpretation of this sub-dimension on the symbolic dimension. While the repeated indicator approach indicates that a higher aggressiveness leads to a lower evaluation of the symbolic dimension and hence to a lower attractiveness of the employer, the two-stage approach indicates that a higher aggressiveness leads to a higher attractiveness. However, the result of the repeated indicator approach seems to be more consistent with theoretical expectations: From an internal perspective, Davies et al. (2004) show that ruthlessness (similar to our aggressiveness construct) negatively influences staff satisfaction, so that it is reasonable to assume that higher (external) aggressiveness perceptions (of the employer brand image) will also lead to lower (external) attractiveness perceptions. In addition, aggressiveness and attractiveness are negatively correlated, suggesting a negative total effect of aggressiveness.

For competitiveness, we cannot determine whether the significant estimate resulting from the two-stage approach or the nonsignificant estimate from the repeated indicator approach is a more reliable finding as we lack evidence on statistical power of the two approaches. However, the repeated indicators estimate is close to zero and the two-stage estimate is substantially larger than zero. Thus, in terms of the precision of estimates, we are inclined to have more confidence in the repeated indicator approach with Mode B since it outperforms the two-stage approach in the simulation study.

Recommendations and guidelines for the use of formative hierarchical latent variable models

In the following, we derive practical guidelines based on the preceding simulation results and the empirical application regarding the use of the different approaches when estimating formative hierarchical latent variables in PLS-SEM. Moreover, we provide guidelines on how researchers should report the results of hierarchical latent variable models and discuss the limitations of this study and opportunities for future research.

When to use which approach?

Overall, the simulation results indicate that the repeated indicator approach with mode B on the higher-order construct and inner path weighting scheme should be used for reflective-formative hierarchical latent variables. This approach produces generally less biased, and therefore, more precise parameter estimates and a more reliable higher-order construct score. In particular, the weights of the lower-order constructs on the higher-order construct and the path coefficient to subsequent endogenous constructs are more precise compared to the other approaches. For a formative higher-order construct, the weights of the lower-order constructs are especially important as they represent actionable drivers of the higher-order construct. This point is also illustrated in

[11] All total effects are significant at $p < .001$, except for aggressiveness which is significant at $p < .10$.

our empirical application in which we show how the first-order constructs contribute to the instrumental and symbolic dimension of an employer brand, and consequently drive the attractiveness of the employer. Hence, they represent strategic key components that managers can influence to improve the perception of their employer image. Misjudging the importance (or even direction) of such weights can have a tremendous long-term impact on the company's strategic employer brand building efforts.

However, there may be situations in which the two-stage approach proves more useful than the repeated indicator approach. First, the two-stage approach can be applied if the researcher is only interested in the higher-level estimates, i.e., the path coefficient to and from the higher-order constructs. In our simulations, the incoming estimate is slightly more precise and the outgoing estimate only slightly worse than the corresponding estimates of the repeated indicator approach with Mode B and path weighting scheme. Moreover, such models are more parsimonious as they only incorporate the focal higher-order level variables. Second, the two-stage approach can be used to assess the nature of the higher-order construct using a confirmatory tetrad analysis (e.g., CTA-PLS) (Gudergan et al., 2008). This approach requires lower-order construct scores as indicators of the higher-order constructs to assess their covariance structure. This assessment could also be achieved with the repeated indicator approach, but it requires an additional analysis of the lower-order construct scores.

Moreover, our simulation results show that neither the repeated indicator approach with Mode B and path weighting scheme, nor the two-stage approach having an unequal number of indicators on the lower-order constructs leads to biased results. In turn, unequal numbers of indicators bias both the results of the repeated indicator approach with measurement mode A and the hybrid approach (regardless of the measurement mode). Nevertheless, the repeated indicator approach with mode B and path weighting scheme is superior to other approaches when the number of indicators is equal.

Reporting guidelines

As noted earlier, PLS-SEM studies often provide limited information regarding the use of hierarchical latent variable models (Ringle et al., 2012). Therefore, we briefly summarize how PLS-SEM studies should be reported when using hierarchical latent variable models. These guidelines aim to help researchers better communicate their PLS-SEM models involving hierarchical latent variables, and to assist reviewers in assessing the appropriateness of the hierarchical latent variable model.

First, researchers should report the type of hierarchical latent variable model, e.g., reflective-formative type, as the model type is crucial for subsequent reporting and for choosing the appropriate modeling approach for the hierarchical latent variable model.

Second, researchers should clearly communicate the approach they use to estimate the hierarchical latent variable model (e.g., repeated indicator or two-stage approach), the mode of measurement (i.e., mode A or mode B) on the higher-order constructs if the repeated indicator approach was applied, and the inner weighting scheme (i.e., centroid, factor or path) used for the PLS-SEM algorithm. Clearly communicating all aspects of the employed approach is especially important as the simulation results described above point to substantial differences between approaches and variations thereof.

Third, researchers should assess the appropriateness of the first-order constructs. The reporting standards should match the conceptual properties of the lower-order constructs, i.e., for reflective constructs, indicator loadings, AVE, composite reliability, discriminant validity, etc., and for formative constructs, indicator weights, significance of weights, multicollinearity of indicators, etc. should be reported (Cenfetelli and Bassellier, 2009; Chin, 1998a; Fornell and Larcker, 1981; Hair et al., 2012; Hair et al., 2012). It is important to note that the weights and loadings which are important for the assessment of this part of the hierarchical latent variable model are obtained from the relation between first-order construct and its manifest variables (indicators).

Fourth, researchers should assess the appropriateness of the higher-order constructs. In line with the former remarks, the assessment should match the conceptual properties of the construct (i.e., reflective or formative) including the subsequent reporting standards. What distinguishes the assessment of higher-order constructs from that of first-order constructs is the role of the weights and loadings in the analysis: they are not obtained from the relations between higher-order construct and manifest variables, but are obtained from the relations between higher-order construct and lower-order constructs. This distinction is especially important if the repeated indicator approach is used, as the weights and loadings are now represented by the path coefficients between higher-order and lower-order constructs, and not by the manifest indicators that are repeated at the construct level.

Limitations and future research

While this study makes important contributions to the understanding of hierarchical latent variables in the PLS-SEM literature, it has its limitations and opens up further avenues for future research.

First, the focus of this manuscript is hierarchical latent variable models with reflective-formative type models and the approaches to estimate such models in PLS-SEM. We examine the reflective-formative type model both in simulations and in an empirical application because this type of hierarchical latent variable model is most frequently applied in research (Ringle et al., 2012). Future research might also investigate the usefulness of the formative-formative type model and the performance of the two approaches to estimate such models. However, in general, the formative-formative type model is less likely used in empirical research (Jarvis et al., 2003; Ringle et al., 2012).

Second, the validity and generalizability of simulation studies are limited by the choice of design factors and factor levels. First, we focused on a simulation design with only one path model of medium complexity and fixed path coefficients. It may be interesting to systematically vary the values of the path coefficients, and to study models with higher complexity (i.e., many endogenous and exogenous variables) and hierarchical latent variables of higher-order. In addition, further insights may be gained from including a first-order construct with a zero weight and testing the statistical power of the approaches (Type I and Type II error rates). Second, future studies could vary the data characteristics, i.e. use non-normal data or multicollinear exogenous variables. However, previous simulations studies have shown a relative high robustness of the PLS-SEM method to these factors (Chin et al., 2003; Henseler and Chin, 2010; Reinartz et al., 2009). Third, we only investigate approaches to estimate hierarchical latent variable models in PLS-SEM. However, it may be interesting to compare the performance of the PLS-SEM approaches to CB-SEM approaches in estimating hierarchical latent variables models. Such a comparison may prove problematic because of restrictions concerning model identification in CB-SEM, especially when formative hierarchical latent variable models are used. A path model with only one endogenous outcome to the hierarchical latent variable as used in our simulations and empirical application would not be identified in a CB-SEM model (Jarvis et al., 2003).

Third, future research could investigate the performance of both approaches to estimate hierarchical latent variable models in PLS-SEM when more complex models such as mediation or moderation models are involved (Wilson, 2010). Particularly models involving a moderation analysis where one of the latent variables involved in the moderation is a hierarchical latent variable may lead to problems in PLS-SEM. Moderation analysis in PLS-SEM is usually carried out with two different approaches that may yield different results depending on how the hierarchical latent variables are estimated: (1) a product-indicator approach and (2) a two-stage approach (Henseler and Chin, 2010). It is unclear how a combination of two approaches for moderation and hierarchical latent variable estimation would perform. There are several possible combinations, e.g., (1) repeated indicator hierarchical latent variable with product indicator moderation, (2) repeated indicator hierarchical latent variable with two-stage moderation, (3) two-stage hierarchical latent variable with product indicator moderation, and (4) two-stage hierarchical latent variable with two-stage moderation, etc., requiring the researcher to chose the combination that most closely resembles the underlying model.

Appendix A. Population model for the simulation

We generate the formative second-order construct as simple linear combination of the first-order constructs with weights of .40, .60 and .70. We set the relation between the exogenous and second-order construct to .66. Therefore, we generate the first-order constructs from the exogenous construct plus structural error ζ. We set the relations from the exogenous construct to the first-order constructs to .40, .60, and .20 which results in the total effect on the second-order constructs of $.4 * .4 + .6 * .6 + .2 * .7 = .66$. In addition, we set the relation from the second-order construct to the final endogenous variable to .60. Finally, we generate the indicators from the construct scores plus measurement error ε. The error variances ε and ζ are set to $\sqrt{1-p^2}$ with p being the parameter of the structural relation or measurement loading (e.g., $\varepsilon = .60$ for loadings of .80 and $\zeta_{FE} = .80 = \sqrt{1-.60^2}$), except for ζ_{SO} which is zero).

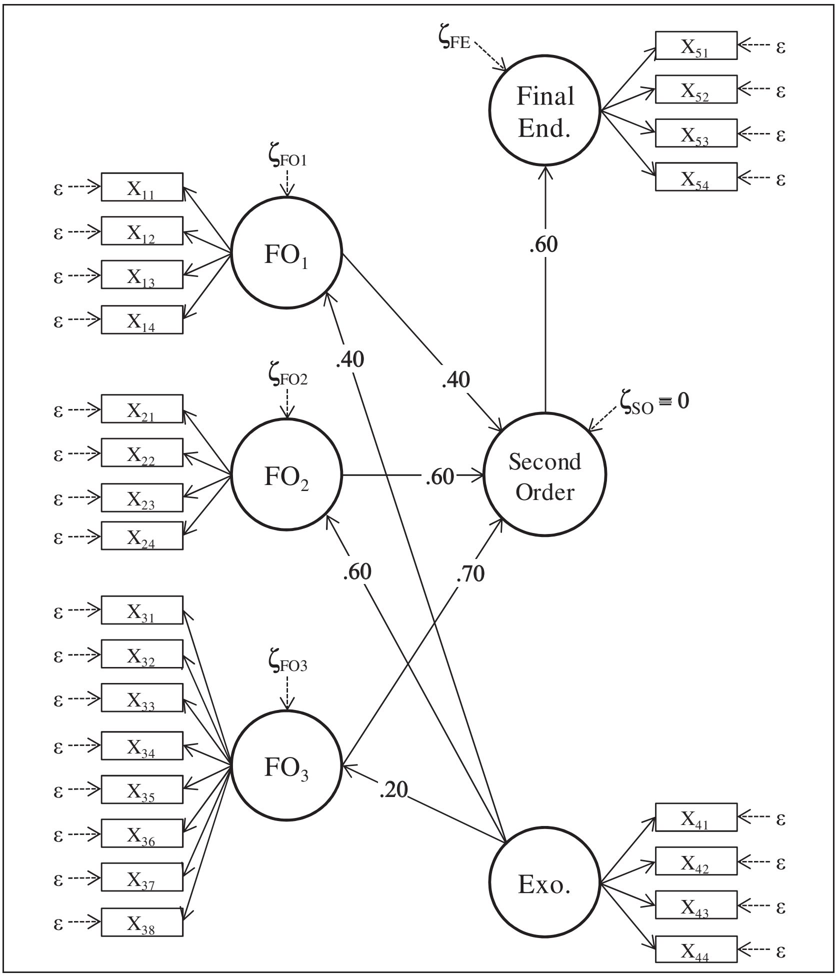

Figure A.1. Population model for the simulation with unequal numbers of indicators

Appendix B. PLS-SEM models of the different approaches

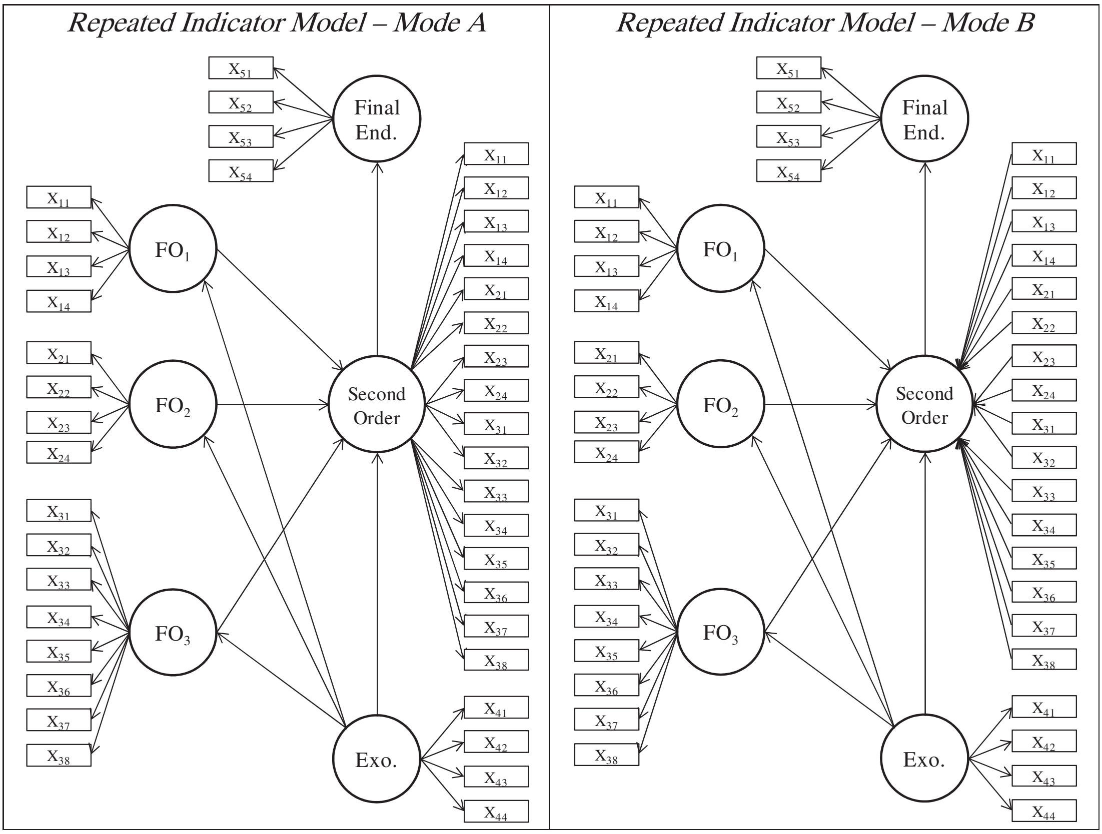

Figure B.1. Repeated indicator Mode A and Mode B PLS-SEM model with unequal numbers of indicators

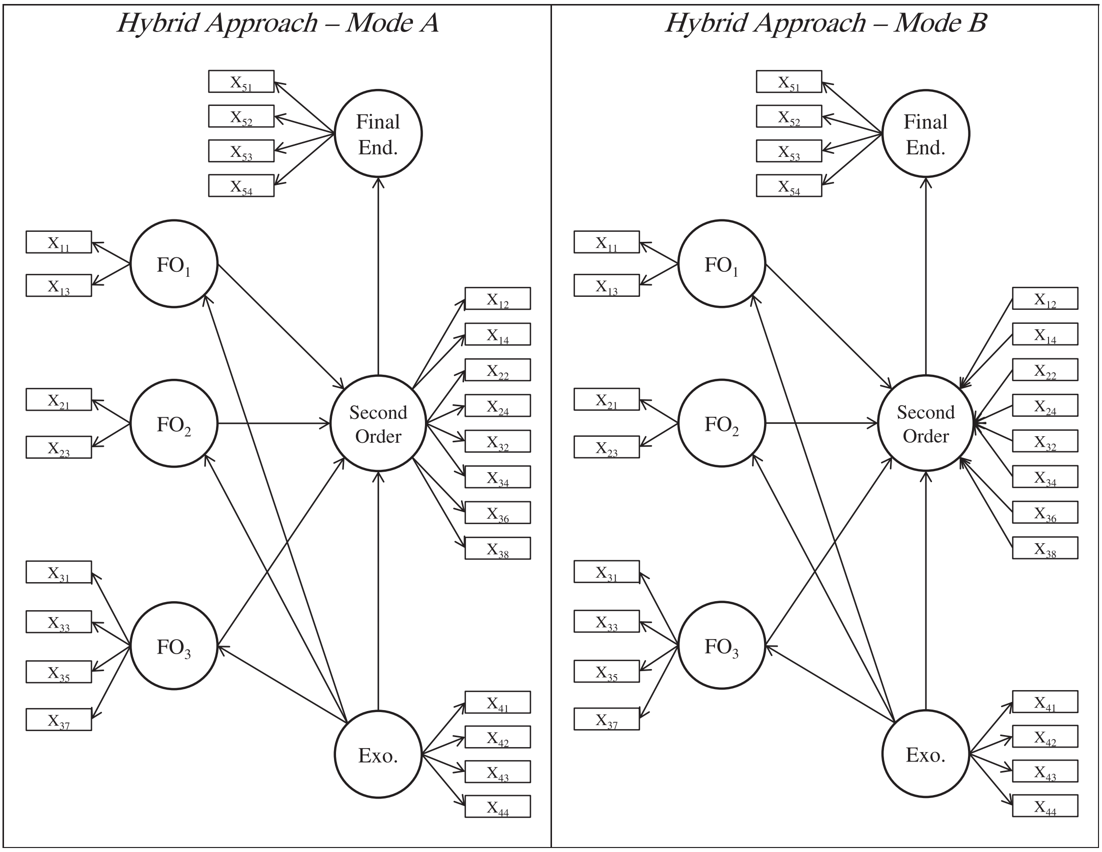

Figure B.2. Hybrid approach Mode A and Mode B PLS-SEM model with unequal numbers of indicators

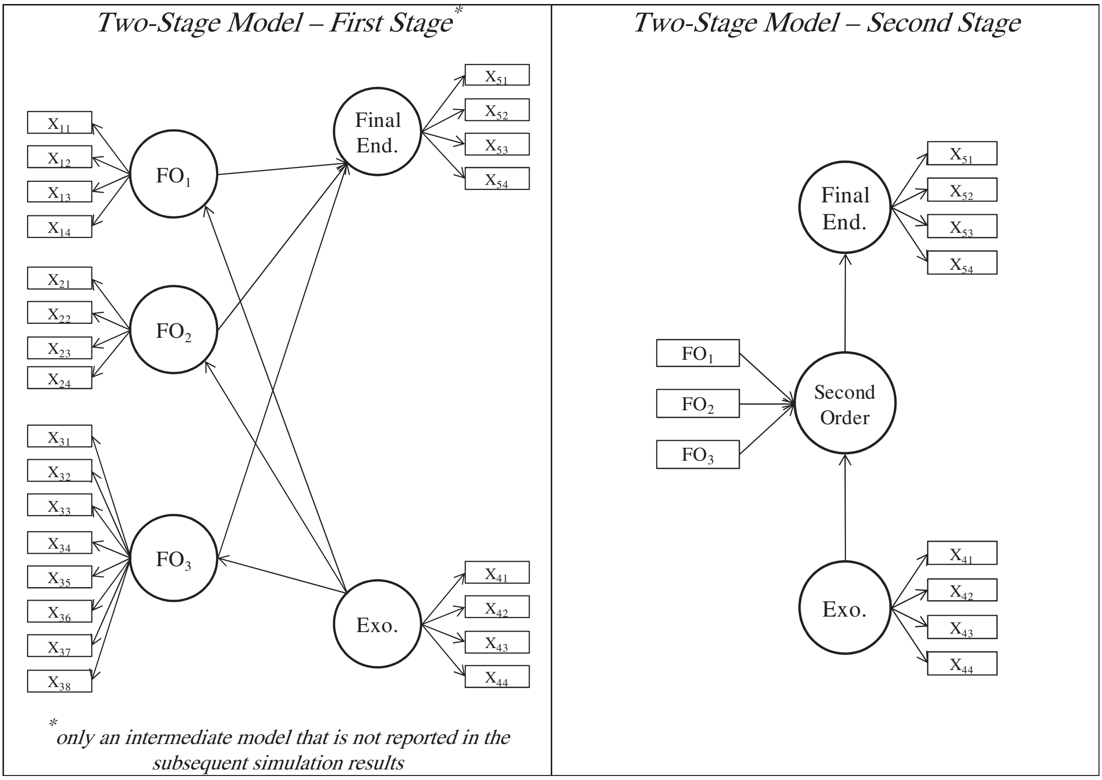

Figure B.3. Two-stage approach PLS-SEM Models with unequal numbers of indicators

Appendix C. MANOVA results for the simulation model

Factor		df	Repeated Indicators Mode B		Repeated Indicators Mode A		Hybrid Mode B		Hybrid Mode A		Two-Stage	
			p-value	Partial η^2	p-value	Partial η^2	p-value	Partial η^2	p-value	Partial η^2	p-value	Partial η^2
Intercept	$Corr^2$	1	.000	1.000	.000	1.000	.000	.999	.000	.999	.000	.999
	RMSE Total	1	.000	.990	.000	.981	.000	.994	.000	.992	.000	.991
	RSE Incoming	1	.000	.912	.000	.943	.000	.931	.000	.952	.000	.870
	RSE Outgoing	1	.000	.765	.000	.788	.000	.840	.000	.855	.000	.785
	RMSE Weights	1	.000	.986	.000	.979	.000	.992	.000	.992	.000	.985
Loadings	$Corr^2$	2	.000	.888	.000	.832	.000	.942	.000	.904	.000	.832
	RMSE Total	2	.000	.318	.000	.135	.000	.864	.000	.710	.000	.093
	RSE Incoming	2	.000	.481	.000	.364	.000	.585	.000	.460	.000	.500
	RSE Outgoing	2	.000	.415	.000	.431	.000	.620	.000	.596	.000	.467
	RMSE Weights	2	.000	.012	.000	.000	.000	.801	.000	.665	.000	.030
Sample Size	$Corr^2$	2	.000	.035	.000	.003	.000	.033	.000	.024	.000	.016
	RMSE Total	2	.000	.127	.000	.012	.000	.115	.000	.050	.000	.049
	RSE Incoming	2	.000	.001	.000	.001	.000	.002	.000	.002	.000	.003
	RSE Outgoing	2	.000	.053	.000	.054	.000	.045	.000	.044	.000	.063
	RMSE Weights	2	.000	.100	.000	.003	.000	.074	.000	.041	.000	.008
Weighting Scheme	$Corr^2$	2	.000	.687	.000	.689	.000	.273	.000	.539	.000	.002
	RMSE Total	2	.000	.787	.000	.634	.000	.107	.000	.530	.000	.003
	RSE Incoming	2	.000	.284	.000	.375	.000	.271	.000	.316	.210	.000
	RSE Outgoing	2	.000	.025	.000	.059	.000	.007	.000	.049	.024	.000
	RMSE Weights	2	.000	.886	.000	.659	.000	.186	.000	.497	.000	.002
Equal	$Corr^2$	1	.000	.293	.000	.003	.000	.566	.000	.132	.000	.234
	RMSE Total	1	.000	.012	.000	.282	.000	.243	.000	.183	.000	.052
	RSE Incoming	1	.867	.000	.000	.685	.000	.078	.000	.653	.629	.000
	RSE Outgoing	1	.000	.009	.000	.001	.000	.043	.000	.004	.000	.010
	RMSE Weights	1	.000	.010	.000	.001	.000	.363	.000	.011	.000	.038

			Repeated Indicators Mode B		Repeated Indicators Mode A		Hybrid Mode B		Hybrid Mode A		Two-Stage	
Factor		**df**	**p-value**	**Partial η^2**	**p-value**	**Partial η^2**	**p-value**	**Partial η^2**	**p-value**	**Partial η^2**	**p-value**	**Partial η^2**
Loadings * Sample Size	Corr^2	4	.177	.000	.000	.001	.000	.026	.000	.027	.326	.000
	RMSE Total	4	.003	.000	.306	.000	.000	.029	.000	.023	.003	.000
	RSE Incoming	4	.000	.000	.421	.000	.000	.001	.000	.001	.000	.002
	RSE Outgoing	4	.000	.022	.000	.012	.000	.020	.000	.009	.000	.018
	RMSE Weights	4	.000	.002	.149	.000	.000	.028	.000	.032	.390	.000
Loadings * Weighting Scheme	Corr^2	4	.000	.009	.000	.002	.000	.127	.000	.040	.000	.000
	RMSE Total	4	.000	.054	.015	.000	.000	.162	.000	.055	.001	.000
	RSE Incoming	4	.000	.002	.000	.002	.000	.004	.000	.007	.178	.000
	RSE Outgoing	4	.000	.025	.000	.006	.000	.002	.000	.002	.690	.000
	RMSE Weights	4	.000	.001	.000	.003	.000	.185	.000	.075	.052	.000
Loadings * Equal	Corr^2	2	.000	.082	.000	.086	.000	.178	.000	.090	.000	.059
	RMSE Total	2	.000	.005	.042	.000	.000	.034	.000	.023	.000	.012
	RSE Incoming	2	.062	.000	.000	.014	.000	.006	.000	.020	.187	.000
	RSE Outgoing	2	.000	.007	.000	.008	.000	.020	.000	.013	.000	.005
	RMSE Weights	2	.000	.003	.000	.001	.000	.057	.000	.026	.000	.009
Sample Size * Weighting Scheme	Corr^2	4	.000	.007	.000	.000	.000	.022	.000	.037	.005	.000
	RMSE Total	4	.000	.082	.771	.000	.000	.020	.000	.026	.001	.000
	RSE Incoming	4	.000	.001	.037	.000	.000	.001	.000	.001	.000	.000
	RSE Outgoing	4	.112	.000	.000	.001	.000	.002	.000	.004	.654	.000
	RMSE Weights	4	.000	.128	.027	.000	.000	.021	.000	.035	.000	.001
Sample Size * Equal	Corr^2	2	.187	.000	.036	.000	.000	.014	.000	.018	.431	.000
	RMSE Total	2	.520	.000	.000	.002	.000	.016	.000	.020	.575	.000
	RSE Incoming	2	.041	.000	.000	.001	.000	.001	.000	.002	.122	.000
	RSE Outgoing	2	.355	.000	.006	.000	.000	.000	.000	.001	.235	.000
	RMSE Weights	2	.361	.000	.000	.000	.000	.015	.000	.020	.230	.000

Factor		df	Repeated Indicators Mode B p-value	Repeated Indicators Mode B Partial η^2	Repeated Indicators Mode A p-value	Repeated Indicators Mode A Partial η^2	Hybrid Mode B p-value	Hybrid Mode B Partial η^2	Hybrid Mode A p-value	Hybrid Mode A Partial η^2	Two-Stage p-value	Two-Stage Partial η^2
Weighting Scheme * Equal	$Corr^2$	2	.000	.003	.000	.793	.000	.131	.000	.644	.633	.000
	RMSE Total	2	.000	.010	.000	.727	.000	.207	.000	.585	.168	.000
	RSE Incoming	2	.000	.001	.000	.305	.000	.060	.000	.246	.462	.000
	RSE Outgoing	2	.112	.000	.000	.094	.000	.007	.000	.071	.775	.000
	RMSE Weights	2	.000	.010	.000	.772	.000	.155	.000	.589	.052	.000
Loadings * Sample Size * Weighting Scheme	$Corr^2$	8	.080	.000	.506	.000	.000	.050	.000	.061	.786	.000
	RMSE Total	8	.641	.000	.395	.000	.000	.052	.000	.045	.733	.000
	RSE Incoming	8	.009	.000	.170	.000	.000	.001	.000	.002	.155	.000
	RSE Outgoing	8	.000	.001	.012	.000	.000	.003	.000	.005	.615	.000
	RMSE Weights	8	.000	.003	.356	.000	.000	.053	.000	.058	.471	.000
Loadings * Sample Size * Equal	$Corr^2$	4	.464	.000	.238	.000	.000	.026	.000	.032	.296	.000
	RMSE Total	4	.340	.000	.025	.000	.000	.027	.000	.022	.176	.000
	RSE Incoming	4	.882	.000	.991	.000	.000	.001	.000	.001	.991	.000
	RSE Outgoing	4	.319	.000	.000	.001	.000	.001	.000	.002	.570	.000
	RMSE Weights	4	.303	.000	.273	.000	.000	.027	.000	.029	.222	.000
Loadings * Weighting Scheme * Equal	$Corr^2$	4	.000	.001	.000	.014	.000	.039	.000	.117	.161	.000
	RMSE Total	4	.000	.001	.000	.005	.000	.032	.000	.135	.957	.000
	RSE Incoming	4	.059	.000	.000	.001	.000	.005	.000	.007	.376	.000
	RSE Outgoing	4	.320	.000	.000	.012	.000	.002	.000	.005	.568	.000
	RMSE Weights	4	.000	.002	.000	.000	.000	.029	.000	.176	.836	.000
Sample Size * Weighting Scheme * Equal	$Corr^2$	4	.009	.000	.016	.000	.000	.026	.000	.028	.019	.000
	RMSE Total	4	.982	.000	.000	.003	.000	.026	.000	.018	.738	.000
	RSE Incoming	4	.648	.000	.010	.000	.001	.000	.000	.001	.365	.000
	RSE Outgoing	4	.828	.000	.000	.001	.000	.002	.000	.002	.627	.000
	RMSE Weights	4	.519	.000	.000	.002	.000	.027	.000	.023	.484	.000

			Repeated Indicators Mode B		Repeated Indicators Mode A		Hybrid Mode B		Hybrid Mode A		Two-Stage	
Factor		**df**	**p-value**	**Partial η^2**	**p-value**	**Partial η^2**	**p-value**	**Partial η^2**	**p-value**	**Partial η^2**	**p-value**	**Partial η^2**
Loadings * Sample Size * Weighting Scheme * Equal	$Corr^2$	8	.661	.000	.356	.000	.000	.049	.000	.063	.897	.000
	RMSE Total	8	.082	.000	.012	.000	.000	.051	.000	.048	.973	.000
	RSE Incoming	8	.562	.000	.249	.000	.000	.001	.000	.003	.671	.000
	RSE Outgoing	8	.091	.000	.000	.001	.000	.003	.000	.007	.312	.000
	RMSE Weights	8	.218	.000	.006	.000	.000	.052	.000	.061	.574	.000
Error	$Corr^2$	53946										
	RMSE Total	53946										
	RSE Incoming	53946										
	RSE Outgoing	53946										
	RMSE Weights	53946										

Note: df = degrees of freedom; RMSE = root mean squared error; $Corr^2$ = squared correlation between true and estimates second-order construct scores.All significant and substantial effects (i.e., all effects that explain more than 5% of the total variance implying a partial η^2 of more than .05) are highlighted in grey.

Appendix D. Additional simulation results

Table D.1. Mean values of path coefficients for the different modeling approaches with different weighting schemes

Inner Weighting Scheme		True model	Repeated indicators Mode B			Repeated indicators Mode A			Hybrid Mode B			Hybrid Mode A			Two-stage		
			Centroid	Factor	Path	Centroid	Factor	Path	Centroid	Factor	Path	Centroid	Factor	Path	Centroid	Factor	Path
Equal	SO → Endo	.60	.56	.55	.57	.56	.55	.56	.54	.53	.54	.53	.53	.54	.55	.55	.55
Number of indicators	FO_1 → SO	.40	.48	.47	.37	.50	.51	.49	.37	.36	.32	.38	.39	.37	.40	.41	.40
	FO_2 → SO	.60	.58	.64	.54	.58	.61	.56	.43	.47	.41	.42	.45	.41	.68	.68	.68
	FO_3 → SO	.70	.48	.40	.62	.45	.39	.49	.37	.32	.44	.35	.31	.38	.41	.41	.41
	Exo → SO	.66	.55	.57	.52	.56	.57	.55	.53	.54	.51	.53	.54	.52	.57	.57	.57
Unequal	SO → Endo	.60	.57	.56	.58	.58	.57	.53	.55	.55	.55	.56	.55	.51	.56	.56	.56
Number of indicators	FO_1 → SO	.40	.47	.46	.36	.39	.32	.20	.36	.34	.26	.30	.24	.16	.40	.40	.40
	FO_2 → SO	.60	.58	.64	.53	.45	.39	.25	.41	.43	.33	.33	.28	.19	.68	.68	.68
	FO_3 → SO	.70	.48	.41	.63	.68	.77	.90	.45	.44	.63	.60	.68	.77	.42	.42	.42
	Exo → SO	.66	.56	.57	.51	.50	.45	.36	.53	.53	.46	.48	.43	.35	.57	.57	.57

Note: Parameter results are mean values combining the factor conditions of 'Loadings' and 'Sample Size'.

Appendix E. Assessment of employer brand image first-order constructs

Table E.1. Quality criteria of the reflective first-order constructs of the instrumental dimension

Construct	Loadings	AVE	Composite reliability
Employer Attractiveness		.78	.95
To me, BRAND_X is an attractive employer.	.92		
BRAND_X would be a good company to work for.	.85		
I would like to work for BRAND_X.	.93		
If BRAND_X was at a job fair, I would seek out their booth.	.81		
I can imagine applying at this company after finishing my studies.	.90		
CSR		.81	.93
BRAND_X is involved in many social projects.	.91		
BRAND_X cares for the environment and is involved in many projects regarding the environment.	.92		
For BRAND_X, doing sustainable business is important.	.88		
Salary		.78	.91
Salaries are attractive at BRAND_X.	.89		
BRAND_X offers a high starting salary.	.89		
BRAND_X pays an above average salary compared to the industry average.	.87		
Career Opportunities		.66	.89
BRAND_X invests heavily in training and development of their employees.	.81		
BRAND_X offers the opportunity to move around the organization and work in different roles and departments.	.83		
BRAND_X offers the opportunity to work and travel abroad.	.77		
At BRAND_X, you have good possibilities for advancement.	.85		
Co-workers		.57	.79
BRAND_X employs people with whom I feel I will have things in common.	.85		
A lot of nice people work at BRAND_X.	.82		
BRAND_X offers an international, diverse working environment with many international colleagues.	.56		
Job Activities		.65	.90
BRAND_X only recruits the best.	.73		
BRAND_X offers variety in the daily work.	.83		
BRAND_X offers a lot of scope for creativity in your work.	.80		
The daily work at BRAND_X offers challenging tasks.	.87		
You receive responsibility at BRAND_X from the very beginning.	.79		
Culture		.71	.91
BRAND_X has a friendly, informal culture.	.84		
At BRAND_X, a familial atmosphere dominates.	.79		
BRAND_X cares about its employees.	.87		
At BRAND_X, a good working atmosphere dominates.	.87		
Competitiveness		.64	.88
BRAND_X has a dynamic, forward-looking approach to their business.	.78		
BRAND_X is successful at the market.	.79		
BRAND_X has a good management.	.83		
BRAND_X offers innovative products.	.80		

(*continued on next page*)

Table E.1 (*continued*)

Construct	Loadings	AVE	Composite reliability
Work-Life Balance		.71	.91
BRAND_X requires you to work standard working hours only.	.75		
BRAND_X offers a relatively stress-free working environment.	.81		
BRAND_X offers a good Work-Life-Balance.	.91		
At BRAND_X, it is easy to reconcile work with family.	.89		

Table E.2. Quality criteria of reflective first-order constructs of the symbolic dimension

Construct	Loadings	AVE	Composite reliability
Sincere		.64	.93
Pleasant	.80		
Sincere	.84		
Honest	.85		
Friendly	.70		
Socially responsible	.77		
Trustworthy	.78		
Reliable	.85		
Aggressive		.61	.90
Aggressive	.77		
Snobbish	.81		
Rugged	.70		
Selfish	.87		
Authoritarian	.63		
Arrogant	.88		
Ambitious		.57	.87
Ambitious	.73		
Leading	.77		
Hard working	.75		
Achievement oriented	.77		
Corporate	.77		
Innovative		.61	.93
Stylish	.80		
Trendy	.82		
Up-to-date	.79		
Innovative	.75		
Young	.74		
Cool	.81		
Imaginative	.71		
Exciting	.82		

Table E.3. Discriminant validity assessment

	Attractiveness	CSR	Career opportunities	Co-workers	Competitiveness	Culture	Job activities	Salary	Work-life balance	Aggressive	Ambitious	Innovative	Sincere
Attractiveness	**.88**												
CSR	.46	**.90**											
Career opportunities	.46	.44	**.81**										
Co-workers	.55	.50	.56	**.75**									
Competitiveness	.38	.37	.62	.51	**.80**								
Culture	.47	.62	.41	.58	.41	**.84**							
Job activities	.53	.43	.66	.54	.54	.41	**.81**						
Salary	.36	.34	.54	.36	.42	.31	.55	**.88**					
Work-life balance	.21	.41	.11	.34	.14	.52	.08	.12	**.84**				
Aggressive	−.25	−.39	−.08	−.32	−.10	−.48	−.10	.02	−.35	**.78**			
Ambitious	.23	.17	.43	.26	.55	.17	.38	.30	−.05	.22	**.76**		
Innovative	.33	.22	.39	.37	.53	.21	.45	.25	−.03	.04	.41	**.78**	
Sincere	.51	.60	.34	.53	.38	.68	.38	.25	.45	−.55	.15	.23	**.80**

Note: Diagonal elements are the square root of AVE and highlighted in bold. Offdiagonal elements are simple bivariate correlations between the constructs.

References

Aaker, J.L., 1997. Dimensions of brand personality. Journal of Marketing Research 34 (3), 347–356.

Agarwal, R., Karahanna, E., 2000. Time flies when you're having fun: cognitive absorption and beliefs about information technology usage. MIS Quarterly 24 (4), 665–694.

Aiman-Smith, L., Bauer, T.N., Cable, D.M., 2001. Are you attracted? Do you intend to pursue? A recruiting policy-capturing study. Journal of Business and Psychology 16 (2), 219–237.

Ambler, T., Barrow, S., 1996. The employer brand. The Journal of Brand Management 4 (3), 185–206.

Backhaus, K.B., Tikoo, S., 2004. Conceptualizing and researching employer branding. Career Development International 9 (5), 501–517.

Barney, J.B., 1991. Firm resources and sustained competitive advantage. Journal of Management 17 (1), 99–120.

Belt, J.A., Paolillo, J.G.P., 1982. The influence of corporate image and specificity of candidate qualifications on response to recruitment advertisement. Journal of Management 8 (1), 105–112.

Birnbaum, D., Somers, M.J., 1993. Fitting job performance into turnover model: an examination of the form of the job performance-turnover relationship and a path model. Journal of Management 19 (1), 1–11.

Black, J.A., Boal, K.B., 1994. Strategic resources: traits, configurations and paths to sustainable competitive advantage. Strategic Management Journal 15 (2), 131–148.

Boyd, B.K., Gove, S., Hitt, M.A., 2005. Construct measurement in strategic management research: illusion or reality? Strategic Management Journal 26 (3), 239–257.

Boyd, B.K., Bergh, D.D., Ketchen Jr., D.J.Jr., 2010. Reconsidering the reputation-performance relationship: a resource-based view. Journal of Management 36 (3), 588–609.

Brayfield, A.H., Rothe, H.F., 1951. An index of job satisfaction. Journal of Applied Psychology 35 (5), 307–311.

Cable, D.M., Turban, D.B., 2003. The value of organizational reputation in the recruitment context: a brand-equity perspective. Journal of Applied Social Psychology 33 (11), 2244–2266.

Cadogan, J.W., Lee, N. Improper use of endogenous formative variables. Journal of Business Research, in press.

Cenfetelli, R.T., Bassellier, G., 2009. Interpretation of formative measurement in information systems research. MIS Quarterly 33 (4), 689–707.

Chacko, T.I., 1983. Research notes. Job and life satisfactions: a causal analysis of their relationships. Academy of Management Journal 26 (1), 163–169.

Chin, W.W., 1998a. The partial least squares approach to structural equation modeling. In: Marcoulides, G.A. (Ed.), Modern Business Research Methods. Lawrence Erlbaum Associates, Mahwah, NJ, pp. 295–336.

Chin, W.W., 1998b. Issues and opinion on structural equation modeling. MIS Quarterly 22 (1), vii–xvi.

Chin, W.W., 2010. How to write up and report PLS analyses. In: Vinzi, V.E., Chin, W.W., Henseler, J., Wang, H. (Eds.), Handbook of Partial Least Squares: Concepts, Methods and Applications in Marketing and Related Fields. Springer, Berlin, pp. 655–690.

Chin, W.W., Marcolin, B.L., Newsted, P.N., 2003. A partial least squares approach for measuring interaction effects: results from a Monte Carlo simulation study and an electronic mail emotion/adoption study. Information Systems Research 14 (2), 189–217.

Davies, G., Chun, R., da Silva, R., Roper, S., 2004. A corporate character scale to assess employee and customer views of organization reputation. Corporate Reputation Review 7 (2), 125–146.

Edwards, J.R., 2001. Multidimensional constructs in organizational behavior research: an integrative analytical framework. Organizational Research Methods 4 (2), 144–192.

Flanagan, D.J., O'Shaughnessy, K.C., 2005. The effect of layoffs on firm reputation. Journal of Management 31 (3), 445–463.

Fornell, C., Larcker, D.F., 1981. Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research 18 (1), 39–50.

Grant, R.M., 1991. The resource-based theory of competitive advantage. California Management Review 33 (3), 114–135.

Gray, E.R., Balmer, J.M.T., 1998. Managing corporate image and corporate reputation. Long Range Planning 31 (5), 695–702.

Grundy, T., 1997. Human resource management: a strategic approach. Long Range Planning 30 (4), 507–517.

Gudergan, S.P., Ringle, C.M., Wende, S., Will, A., 2008. Confirmatory tetrad analysis in PLS path modeling. Journal of Business Research 61 (12), 1238–1249.

Hair, J.F, Sarstedt, M., Pieper, T., Ringle, C.M., 2012. The use of partial least squares structural equation modeling in strategic management research: a review of past practices and recommendations for future applications. Long Range Planning 45, 320–340.
Hair, J., Sarstedt, M., Ringle, C.M., Mena, J., 2012. An assessment of the use of partial least squares structural equation modeling in marketing research. Journal of the Academy of Marketing Science 40 (3), 414–433.
Henseler, J., Ringle, C.M., Sinkovics, R.R., 2009. The use of partial least squares path modeling in international marketing. In: Sinkovics, R.R., Ghauri, P.N. (Eds.), Advances in International Marketing. Emerald, Bingley, pp. 277–319.
Henseler, J., Chin, W.W., 2010. A comparison of approaches for the analysis of interaction effects between latent variables using partial least squares path modeling. Structural Equation Modeling: A Multidisciplinary Journal 17 (1), 82–109.
Jarvis, D., MacKenzie, S., Podsakoff, P., 2003. A critical review of construct indicators and measurement model misspecification in marketing and consumer research. Journal of Consumer Research 30 (3), 199–218.
Johnson, R.E., Rosen, C.C., Chang, C.-H., Djurdjevic, E., Taing, M.U., 2012. Recommendations for improving the construct clarity of higher-order multidimensional constructs. Human Resource Management Review 22 (2), 62–72.
Keller, K., 1993. Conceptualizing, measuring, managing customer-based brand equity. Journal of Marketing 57 (1), 1–22.
Ketchen Jr., D.J.Jr., Boyd, B.K., Bergh, D.D., 2008. Research methodology in strategic management: past accomplishments and future challenges. Organizational Research Methods 11 (4), 643–658.
Kim, K.H., Joo Jeon, B., Jung, H.S., Lu, W., Jones, J., 2011. Effective employment brand equity through sustainable competitive advantage, marketing strategy, and corporate image. Journal of Business Research 64 (11), 1207–1211.
Knox, S., Freeman, C., 2006. Measuring and managing employer brand image in the service industry. Journal of Marketing Management 22 (7/8), 695–716.
Koka, B.R., Prescott, J.E., 2002. Strategic alliances as social capital: a multidimensional view. Strategic Management Journal 23 (9), 795–816.
Law, K.S., Wong, C., Mobley, W.H., 1998. Toward a taxonomy of multidimensional constructs. Academy of Management Review 23 (4), 741–755.
Law, K.S., Wong, C.-S., 1999. Multidimensional constructs in structural equation analysis: an illustration using the job perception and job satisfaction constructs. Journal of Management 25 (2), 143–160.
Lee, N., Cadogan, J.W. Problems with formative and higher-order reflective variables. Journal of Business Research, in press.
Lievens, F., Highhouse, S., 2003. The relation of instrumental and symbolic attributes to a company's attractiveness as an employer. Personnel Psychology 56 (1), 75–102.
Lohmöller, J.-B., 1989. Latent Variable Path Modeling with Partial Least Squares. Physica-Verlag, Heidelberg, Germany.
MacKenzie, S.B., Podsakoff, P.M., Podsakoff, N.P., 2011. Construct measurement and validation procedures in mis and behavioral research: integrating new and existing techniques. MIS Quarterly 35 (2), 293–334.
Maltz, A.C., Shenhar, A.J., Reilly, R.R., 2003. Beyond the balanced scorecard: refining the search for organizational success measures. Long Range Planning 36 (2), 187–204.
Netemeyer, R.G., Bearden, W.O., Sharma, S., 2003. Scaling Procedures: Issues and Applications. Sage Publications, Thousand Oaks.
Noonan, R., Wold, H., 1983. Evaluating school systems using partial least squares. Evaluation in Education 7, 219–364.
Petter, S., Straub, D., Rai, A., 2007. Specifying formative constructs in information systems research. MIS Quarterly 31 (1), 623–656.
Podsakoff, N.P., Shen, W., Podsakoff, P.M., 2006. The role of formative measurement models in strategic management research: review, critique, and implications for future research. In: Ketchen, A., Bergh, D.D. (Eds.), Research Methodology in Strategy and Management, vol. 3. Emerald Group Publishing Limited, pp. 197–252.
Polites, G.L., Roberts, N., Thatcher, J., 2012. Conceptualizing models using multidimensional constructs: a review and guidelines for their use. European Journal of Information Systems 21 (1), 22–48.
Preacher, K.J., Hayes, A.F., 2008. Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior Research Methods 40 (3), 879–891.

Quinn, R., Staines, G., 1979. The 1977 Quality of Employment Survey. Institute for Social Research, Ann Arbor, MI.

Reinartz, W.J., Haenlein, M., Henseler, J., 2009. An empirical comparison of the efficacy of covariance-based and variance-based SEM. International Journal of Research in Marketing 26 (4), 332—344.

Rindova, V., Williamson, I., Petkova, A., Sever, J., 2005. Being good or being known: an empirical examination of the dimensions, antecedents, and consequences of organizational reputation. Academy of Management Journal 48 (6), 1033—1050.

Rindova, V., Williamson, I., Petkova, A., 2010. When is reputation an asset? Reflections on theory and methods in two studies of business schools. Journal of Management 36 (3), 610—619.

Rindskopf, D., Rose, T., 1988. Second order factor analysis: some theory and applications. Multivariate Behavioral Research 23 (1), 51—67.

Ringle, C.M., Sarstedt, M., Straub, D.W., 2012. Editor's comments: a critical look at the use of PLS-SEM in MIS quarterly. MIS Quarterly 36 (1), iii—xiv.

Ringle, C.M., Wende, S., Will, A., 2005. SmartPLS 2.0 (Beta) Hamburg. Available at: http://www.smartpls.de.

Roberts, P.W., Dowling, G.R., 2002. Corporate reputation and sustained financial performance. Strategic Management Journal 23 (12), 1077—1093.

Rynes, S.L., 1991. Recruitment, job choice, and post-hire consequences: a call for new research directions. In: Dunnette, M.D., Hough, L.M. (Eds.), Handbook of Industrial and Organizational Psychology, vol. 2, Palo Alto, California, pp. 399—444.

Schwaiger, M., Sarstedt, M., Taylor, C.R., 2010. Art for the sake of the corporation. Journal of Advertising Research 50 (1), 77—90.

Shrout, P.E., Bolger, N., 2002. Mediation in experimental and nonexperimental studies: new procedures and recommendations. Psychological Methods 7 (4), 422—455.

Slaughter, J.E., Greguras, G.J., 2009. Initial Attraction to organizations: the influence of trait inferences. International Journal of Selection and Assessment 17 (1), 1—18.

Sullivan, J., 2004. Eight Elements of a Successful Employment Brand. Available at: http://www.ere.net/2004/02/23/the-8-elements-of-a-successful-employment-brand/.

Tanriverdi, H., Venkatraman, N., 2005. Knowledge relatedness and the performance of multibusiness firms. Strategic Management Journal 26 (2), 97—119.

Tenenhaus, M., Vinzi, V.E., Chatelin, Y.-M., Lauro, C., 2005. PLS path modeling. Computational Statistics & Data Analysis 48 (1), 159—205.

Tüzüner, V.L., Yüksel, C.A., 2009. Segmenting potential employees according to firms' employer attractiveness dimensions in the employer branding concept. Journal of Academic Research in Economics 1 (1), 47—62.

Venkatraman, N., 1989. Strategic orientation of business enterprises: the construct, dimensionality, and measurement. Management Science 35 (8), 942—962.

Venkatraman, N., Ramanunjam, V., 1986. Measurement of business performance in strategy research: a comparison of performance. Academy of Management Review 11 (4), 801—814.

Weiss, A.M., Anderson, E., MacInnis, D.J., 1999. Reputation management as a motivation for sales structure decisions. Journal of Marketing 63 (4), 74—89.

Wetzels, M., Odekerken-Schröder, G., van Oppen, C., 2009. Using PLS path modeling for assessing hierarchical construct models: guidelines and empirical illustration. MIS Quarterly 33 (1), 177—195.

Wilson, B., 2010. Using PLS to investigate interaction effects between higher order branding constructs. In: Vinzi, V.E., Chin, W.W., Henseler, J., Wang, H. (Eds.), Handbook of Partial Least Squares: Concepts, Methods and Applications in Marketing and Related Fields. Springer, Berlin, pp. 621—652.

Wilson, B., Henseler, J., 2007. Modeling Reflective Higher-order Constructs Using Three Approaches with PLS Path Modeling: A Monte Carlo Comparison. Australian and New Zealand Marketing Academy Conference, Otago, Australia, pp. 791—800.

Wold, H., 1982. Soft modeling: the basic design and some extensions. In: Jöreskog, K.G., Wold, H. (Eds.), Systems under Indirect Observation: Causality, Structure, Prediction, vol. 2. North Holland, Amsterdam, pp. 1—54.

Wright, P.M., McMahan, G.C., 1992. Theoretical perspectives for strategic human resource management. Journal of Management 18 (2), 295—320.

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