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Causal versus reflective specification. A methodological review of structural equation modeling in marketing

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Theoretical concepts can be operationalized in causal as well as in reflective form, but almost exclusively the reflective measurement models were prevalent in the literature for a long time. The fact that the covariance-based measurements and the reflective operationalization of latent variables have become widespread is explained with the dominant role of classical test theory in empirical research.

The present paper aims to present some of the most important methodological issues related to causal or reflective specification. As the authors are marketing professionals and due to the fact that in marketing literature specification related issues affect mainly SEM (structural equation modeling) applications, the paper presents the specification related issues through the SEM methodology.

Keywords: structural equation modeling (SEM), customer-based brand equity, causal specification, reflective specification.

JEL code: C30.

Introduction

Modeling built on structural equations has increased in popularity in marketing research (Yoo et al. 2000; Berács et al. 2003; Vázquez et al. 2002; Erdem et al. 2006; Netemeyer et al. 2004). Nowadays there is no significant marketing magazine issue without researches built on SEM (Baumgartner and Homburg 1996; Steenkamp and Baumgartner 2000; Babin et al. 2008). Despite its growing popularity, it has not become as widespread in marketing as in other sciences.

The meta-analysis of incorrect operationalization carried out by Jarvis et al. (2003) covers four significant marketing magazines (*Journal*

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of Consumer Research, *Journal of Marketing*, *Journal of Marketing Research* and *Marketing Science*). According to their results, 71% of the examined 1192 latent constructs were correctly modeled. The majority of the remaining 29% incorrectly operationalized latent constructs were formative[3] concepts modeled by the authors as reflective ones.

Our paper presents a methodological review of causal versus reflective specification. The problem of specification is a main issue in structural equation modeling (SEM) applications, thus we present the most important methodological problems of specification in the structural equation modeling framework. We exemplify SEM estimation with the help of a consumer-based brand equity model.

We use the terminology suggested by Bollen (2011). According to this, measurement models fall into three categories:

- Reflective models. Their indicators are determined by the latent variable. In their graphic illustration, the arrows are directed from the latent variable towards the indicators.
- Causal models. The latent variable is determined by the indicators. In their graphic illustration, the arrows are directed from the indicators towards the latent variable.
- Composite (Formative) measurement models. The composite variable is determined by the indicators. In their graphic illustration, the arrows are directed from the indicators towards the composite variable.

There are substantive differences between the causal and formative measurement models (Jarvis et al. 2003; Bollen 2011). In causal measurement, we can estimate a latent variable, while this is impossible in the composite measurement models where we can estimate composite (formative) notions. From a mathematical point of view, the substantive difference lies in the disturbance term estimated at the level of the latent indicator, which is not present in the composite models. As a consequence, in the latter model the researcher has to

[3] The authors do not make clear if they are referring to causal or composite indicators.

ensure the inclusion of all indicators explaining the notion in the analysis since he estimates the given composite notion without any error term.

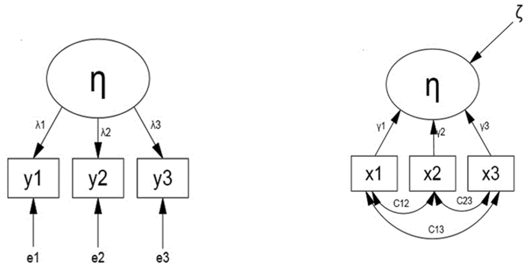
At Bollen's suggestion (2011) we will try to avoid the use of the formative notion because it has often been used in the literature to denote (causal) measurement models with real latent variable and (composite) measurement models as well.

To estimate causal models with latent variable, estimators (maximum likelihood by default) ensured by covariance-based software (Amos, EQS and Lisrel) are suitable, while a popular way to estimate the composite measurement models is PLS (Smart PLS).

Causal versus reflective models

We are able to operationalize theoretical concepts in causal as well as reflective forms (Jarvis et al. 2003; Temme and Hildebrandt 2006), but almost exclusively the reflective measurement models were prevalent in the literature for a long time. While reflective models dominate the scientific literature of psychology and management, the causal and composite approach plays a greater role in economic sciences and sociology (Borsboom et al. 2003; Coltman et al. 2008). Typical examples of reflective measurement models are attitude or willingness to purchase (Jarvis et al. 2003). Both attitude and willingness to purchase are rightfully assumed to signal unobservable states that influence measurable phenomena. Typical example of composite measurement models might be "quality of life" (Bollen and Ting 2000). Quality of life could be measured by factors such as health, happiness, economic situation, but the assumption that they would be the effects of the quality of life is not theoretically grounded (Bollen and Ting 2000).

In the case of the reflective measurement models we assume that the causal processes are directed from the latent variable towards the indicators. That is, we assume that the change in the latent variable will also cause a change in the indicators (Bollen and Lennox 1991; Jarvis et al. 2003; Coltman et al. 2008). In the graphical illustration, the arrows are directed from the ellipse standing for the latent variable towards the squares standing for the indicators (measured variables).



Reflective model Causal model

Source: Bollen and Lennox (1991)

Figure 1: Schematic illustration of reflective and causal measurement models

In the causal measurement models the direction of the causal process is the exact opposite to that of the reflective one. In this case we assume that the change in the indicators leads to change in the latent variable (Jarvis et al. 2003). In the graphical illustration, the arrows are directed from the indicators to the ellipse standing for the latent variable. We argue that the causal latent variable is created by the common variance of the indicators.

According to the above model, the equation of the reflective measurement model can be written as follows:

$$y_i = \lambda_i \eta + \varepsilon_i$$

where y_i is the ith indicator of the reflective η latent variable, ε_i is the measurement error belonging to the ith indicator, and λ_i parameter is the effect of the η latent variable on y_i.

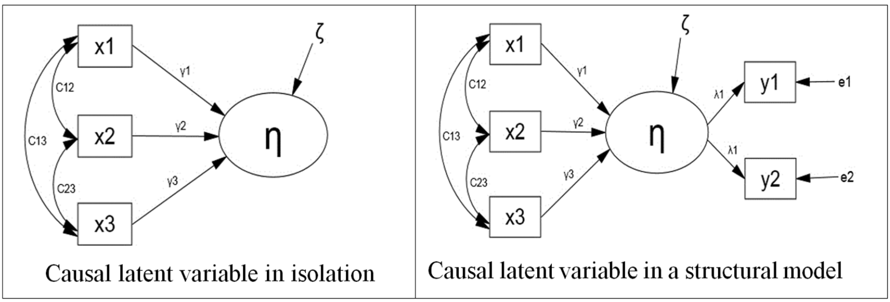
We assume that measurement errors are independent from each other (that is, $cov(\varepsilon_i, \varepsilon_j) = 0$, and $i \neq j$), and they are independent from the latent variable (that is, $cov(\eta, \varepsilon_i) = 0$). Further on, in reflective models there must be a positive intercorrelation between indicators. This assumption was proved by Bollen (1984), starting from the conclusions of Curtis and Jackson's (1962) article.

The causal model can be illustrated with the following equation:

$$\eta = \sum_{i=1}^{n} \gamma_i x_i + \zeta$$

where x_i is the ith causal indicator, the γ_i parameter measures the effect of the ith indicator on the η latent variable, while ζ is the disturbance effect belonging to the latent variable. There is no correlation between the disturbance effect and indicators (that is, $\mathrm{cov}(x_i, \zeta) = 0$). The meaning of the disturbance effect has been explained in several ways. According to Jarvis et al. (2003), the disturbance effect is the joint error of the measured variables, while according to MacKenzie et al. (2005) it may come from three sources: the measurement error of indicators, the interaction between indicators and it can also be a part of the construct not explained by the indicators.

Diamantopoulos (2006) proved that the disturbance effect cannot be explained with the measurement error, since the causal indicators per definition take part in the estimation without errors. The only acceptable explanation is that disturbance consists of the variance unexplained by the latent variable.



Source: own design (based on Bollen and Lennox 1991 and Diamantopoulos et al. 2008).

Figure 2: Causal latent variable in isolation and in a structural model

In the case of reflective models positive correlation between the indicators is a requirement (Diamantopoulos et al. 2008). We make it possible for causal indicators to freely correlate in the model, but they are also expected to share some content since they influence a latent variable together; consequently, we expect the correlation between indicators to be positive (Bollen 2011).

Causal indicators cannot replace each other, all of them measuring a specific area of the concept. If we leave any of the indicators out, we change the meaning of the concept as well (Jarvis et al. 2003; Diamantopoulos et al. 2008). As opposed to this, if we leave any of the indicators out of the reflective model, we do not risk modifying the meaning of the concept (Jarvis et al. 2003).

Reflective measurement models can be correctly estimated in isolation (Diamantopoulos et al. 2008), while causal measurement models cannot be used in isolation; therefore they cannot be estimated (Jarvis et al. 2003; Bollen and Lennox 1991; MacKenzie et al. 2005). In order to estimate disturbance at the level of the latent variable, we have to include the causal measurement model in a larger model. More exactly, we need a complete structural model for correct estimation. A widely accepted solution to the problem is to estimate the causal latent variable together with its consequences within a structural model. More precisely, in order to estimate disturbance at the level of the latent concept, it is necessary that two arrows be directed from the causal latent concept towards two reflective indicators or latent variables (Jöreskog and Goldberger 1975; MacKenzie et al. 2005).

Preparing, testing and fitting the structural equations

One could estimate structural equations with covariance (e.g. Amos, Lisrel, Mplus) or variance (e.g. SmartPLS) based methods. In spite of difficulties, covariance-based estimation procedures are more reliable and do not have the deficiencies of a PLS-PM. It is important to mention that an analyzing method similar to the structural equation models is the neural network whose possibilities are not dealt with by the present paper. The comparison between SEM and neural networks was carried out by Davies et al. (1999).

The advantage of the PLS-based models is that they give a stable estimation even when the requirements of the covariance-based models (Amos, Lisrel), such as the required size of the sample or normal distribution, are not met (Henseler et al. 2009).

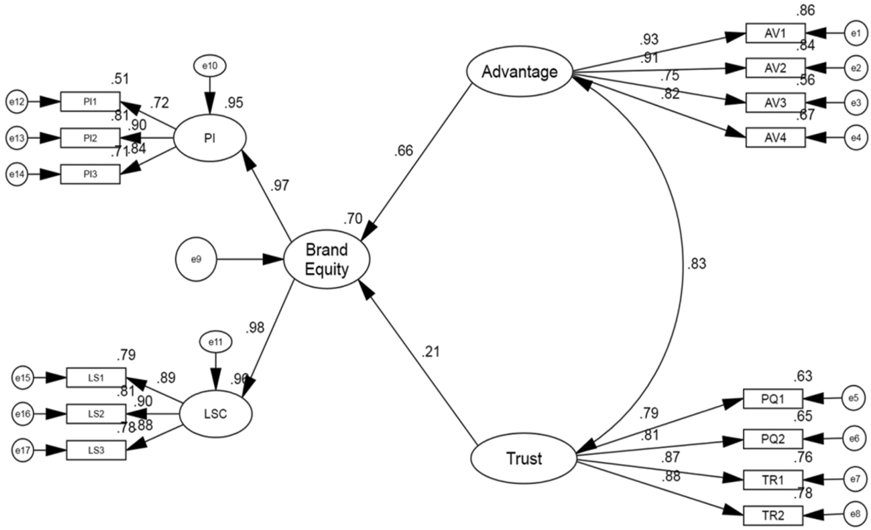
Further on, the PLS-PM is equally suitable for estimating both the reflective and causal models (Wilson et al. 2007; Reinartz et al. 2009). Moreover, according to some authors, the estimation of causal (composite) measurement models are only possible under PLS conditions (Alpert et al. 2001). But since we do not estimate disturbance (error) in PLS, we practically measure composite variables rather than latent ones with the indicators.

Covariance-based estimations (Amos, Lisrel, Mplus), as opposed to PLS, estimate parameters more accurately (Reinartz et al. 2009), so if assumptions of normality and large samples are met, the formers are proposed to be chosen. A deficiency of the PLS estimation is that it does not minimize any criterion (Goffin 2007). As the PLS does not impose any strict requirement towards data, it does not make any general test referring to the goodness of fit and it can exclusively be applied to recursive models, that is, reflexive and reciprocal effects cannot be estimated (Temme and Hildebrandt 2006).

Brief exemplification – Consumer-based brand equity

In the following part we exemplify the casual-reflexive discussion through a consumer-based brand-equity (CBBE) model, presented in Figure 3. Because this model is helping to understand whether a specification is reflective or casual, this time we do not report about data collection, sample and analysis. We present only the model, assessment of reliability and report proposed fit indicators.

We define consumer-based brand equity as a second-order latent variable. As a consequence, we assume that consumer-based brand equity is a concept caused by various factors. We assume that the dimensions of consumer-based brand equity have to be estimated in a reflective measurement model. Well-structured communication campaigns are able to induce trust in a brand. In this sense, measuring trust with causal indicators may be well-grounded, since trust is the effect of experience, of convincing accounts of acquaintances, etc. (variables PQ1, PQ2, TR1, TR2). However, in survey based data collection we measure latent concepts by asking the interviewees about brand-related associations already present in their mind (variables AV1, AV2, AV3, AV4). When the respondents answer questions related to benefits or perceived quality, their already existent ideas about the benefits and quality will manifest. In this case, the only suitable method for measuring consumer-based brand equity dimensions is measuring with reflective indicators.



Source: own design

Figure 3. Causally measured consumer based brand equity (standardized version)

On the other hand, consumer-based brand equity is a theoretical term, thus consumers do not have already existing ideas about this concept and consequently CBBE can have no reflections. The substantive formulations essential from the viewpoint of the causal specification of consumer-based brand equity: brand adds value to the product (Farquhar 1989; Achenbaum 1993), brand equity is defined as the totality of intangible brand assets (Aaker 1991). Consequently, theory regards brand equity as something that comes into being due to the associations linked to the brand name.

Our assumptions regarding the structure of the consumer-based brand equity and its consequences are tested using the basic fitting indicators of SEM, and the reliability and validity of the theoretical constructs are assessed following Hair et al. (2009).

Table 1 provides the results from the assessment of overall fit. The TLI and CFI exceed the conservative 0.95 boundary as well, the relative chi-square corresponds to the requirement Hair et al. (2009) formulates, the RMSEA value is good, and SRMR qualifies as outstanding (0.034).

Table 1. Fit statistics of the causally measured consumer based brand equity

Goodness of fit					
	$\chi 2$	DF	TLI	CFI	RMSEA
Brand	198	72	0.96	0.97	0.08

Source: own calculations

As the model operationalizes first order latent variables in reflective measurement models, the assessment of reliability and validity is possible with classical test theory. The standardized regression weights (SRW) and the squared multiple correlations (SMC) measure the reliability and validity of indicators, whereas the composite reliability (CR) and average variance extracted (AVE) measure the reliability and validity of latent variables. Amos does not print in the output the latter two indicators, but the formulas from Hair et al. (2009) enable to compute them. The squared multiple correlations for every indicator exceed the 0.5 value and the standardized coefficients all exceed the 0.7 value, all this indicates convergent validity. In the case of all the four latent variables, the CR exceeds 0.7 and similarly, the AVE exceeds 0.5, indicating that the variables of the model correctly map the contents of the dimensions.

Table 2. Convergent validity test

	CR	*AVE*	*SRW*	*SMC*
Advantage	0.91	0.73		
AV1			0.93	0.86
AV2			0.91	0.82
AV3			0.75	0.56
AV4			0.82	0.67
Trust	0.91	0.71		
PQ1			0.79	0.63
PQ2			0.81	0.66
TR1			0.87	0.76
TR2			0.88	0.78
Purchase intention	0.86	0.67		
PI1			0.71	0.51
PI2			0.9	0.81
PI3			0.84	0.71
Low search cost	0.92	0.79		
LSC1			0.89	0.79
LSC2			0.9	0.81
LSC3			0.88	0.78

Source: own calculations

The assessment of the model provides support for discrimination as all AVE are greater than the shared variance. From the perspective of the brand equity model a less important issue is the lack of discriminant validity between the consequences of the measured brand's brand equity. By including the consequences as composite variables the problem disappears, and the assessment of external validity offers other solution to this issue.

The validity assessment of causal measures is a controversial topic (Diamantopoulos et al. 2008). This study, contrary to skepticism related to the applicability of statistical procedures, stresses the importance of establishment of validity (Edwards and Bagozzi 2000). The study manages to assess the validity following the recommendations of Diamantopoulos et al. (2008) and Bollen (2011).

The present model determines the causal relationships at the level of structural relationships, as first level latent variables causally determine the second level brand equity. The significant γ-s indicates the validity of the first level causal measures (Advantage and Trust (in quality)) (Diamantopoulos et al. 2008, Bollen 2011). Another test of validity is to examine the overall fit (Bollen 2011). Table 1 provides evidence for excellent fit.

The positive sign of high values of path estimates (Figure 3) supports external validity for every model (Bollen 2011). Moreover, testing the model with other latent variables as Loyalty and OBE provides further evidence of external validity, as the fit indices represent a very good fit (χ^2=244, df=88, TLI=.955, CFI=.963, RMSEA=.075). Following certain recommendations of Diamantopoulos et al. (2008) this study considers the disturbance term (ζ) one of the most important indicators of construct validity. The standardized value of the disturbance provides information about variance explained. The two-dimensional structure is able to explain 70% of the brand equity dimension variance supporting construct validity.

Conclusion

SEM is an outstanding tool in the cases when building the model takes place within a precisely defined theoretical framework and when the model is of medium complexity (Baumgartner and Homburg 1996). SEM is a less suitable tool for analysis in the first opening stage of model building, that is, it shows its real force when the researcher has properly clear ideas or theoretical assumptions regarding the relationships between the variables included in the analysis. Baumgartner and Homburg (1996) lay great stress on the prior analysis of data, identification of outstanding values, carrying out normality tests etc.

Since even literature knows little about testing causal models, there is a great need for the conscious building and use of causal models where it is theoretically grounded (Diamantopoulos et al. 2008).

It is important to formulate that we have to pay special attention to one of the biasing factors of measuring brand related concepts in future researches. When measuring such concepts, we ask brand-related questions, and as a consequence of the *halo* effect and the common method they might also share variances that are due to the brand and the method rather than the specific contents of the questions.

All this might have an important consequence, namely that when we use reflective specification, we will be able to fit several valid concepts on our model, since these will share common variance due to the halo effect and the common method. In a causal model we have to allow the exogenous variables to correlate, thus light is shed onto this problem in assessing fit; in the reflective specification, however, the dimensions are endogenous variables and they do not have to correlate freely; this way, several consumer-based brand equity models can be built without us knowing which of the dimensions are the ones that can cause something together.

References

Aaker, D. A. 1991. *Managing Brand Equity: Capitalizing on the Value of a Brand Name*. New York: Free Press.

Achenbaum, A. A. 1993. The mismanagement of brand equity. In: Lewis, I. M. (ed.) *ARF Fifth Annual Advertising and Promotion Workshop*, Pennsylvania: The New York Hilton.

Babin, B. J.–Hair, J. F.–Boles, J. S. 2008. Publishing Research in Marketing Journals Using Structural Equation Modelling. *Journal of Marketing Theory and Practice* 16(4), 279-285.

Baumgartner, H.–Homburg, C. 1996. Applications of Structural Equation Modeling in Marketing and Consumer Research: A Review. *International Journal of Research in Marketing* 13(2), 139-161.

Berács J.–Hooley G.–Sajtos L.–Keszey T. 2003. Marketing-erőforrások koncepcionális megközelítése. *Vezetéstudomány* 34(2), 2-13.

Bollen, K. 2011. Evaluating effect, composite, and causal indicators in structural equation models. *MIS Quarterly* 35(2), 359-372.

Borsboom, D.–Mellenbergh, G. J.–Heerden, J. 2003. The Theoretical Status of Latent Variables. *Psychological Review* 110(2), 203-19.

Coltman, T.–Devinney, T. M.–Midgley, D. F.–Venaik, S. 2008. Formative Versus Reflective Measurement Models: Two Applications of Formative Measurement. *Journal of Business Research* 61(12), 1250-1262.

Curtis, R. F.–Jackson, E. F. 1962. Multiple Indicators in Survey Research. *American Journal of Sociology* 68(2), 195-204.

Davies, F.–Goode, M.–Mazanec, J.–Moutinho, L. 1999. LISREL and Neural Network Modelling: Two Comparison Studies. *Journal of Retailing and Consumer Services* 6(4), 249-261.

Diamantopoulos, A. 2006. The Error in Formative Measurement Models: Interpretation and Modeling Implications. *Journal of Modelling in Management* 1(1), 7-17.

Diamantopoulos, A.–Siguaw, J. A. 2006. Formative Versus Reflective Indicators in Organizational Measure Development: A Comparison and Empirical Illustration. *British Journal of Management* 17(4), 262-282.

Diamantopoulos, A.–Riefler, P.–Roth, K. P. 2008. Advancing Formative Measurement Models. *Journal of Business Research* 61(12), 1203-1218.

Edwards, J. R.–Bagozzi, R. P. 2000. On the Nature and Direction of Relationships Between Constructs and Measures. *Psychological Methods* 5(2), 155-174.

Erdem, T.–Swait, J.–Valenzuela, A. 2006. Brands as signals: a cross-country validation study. *Journal of Marketing* 70(1), 34-49.

Farquhar, P. H. 1989. Managing brand equity. *Marketing Research* 1(3), 24-33.

Goffin, R. D. 2007. Assessing the Adequacy of Structural Equation Models: Golden Rules and Editorial Policies. *Personality and Individual Differences* 42(5), 831-839.

Hair, J. F.–Anderson, R.–Tatham, R.–Black, W. 2009. *Multivariate Data Analysis*. Prentice Hall: New York.

Henseler, J.–Ringle, C. M.–Sinkovics, R. R. 2009. The Use of Partial Least Squares Path Modeling in International Marketing. *Advances in International Marketing* 20, 277-319.

Jarvis, C. B.–Mackenzie, S. B.–Podsakoff, P. M. 2003. A Critical Review of Construct Indicators and Measurement Model Misspecification in Marketing and Consumer Research. *Journal of Consumer Research* 30(2), 199-218.

Jöreskog, K. G.–Goldberger, A. S. 1975. Estimation of a Model with Multiple Indicators and Multiple Causes of a Single Latent Variable. *Journal of the American Statistical Association*, 70(351), 631-639.

Netemeyer, R. G.–Krishnan, B.–Pullig, C.–Wang, G.–Yagci, M.–Dean, D.–Ricks, J.–Wirth, F. 2004. Developing and validating measures of facets of customer-based brand equity. *Journal of Business Research* 57(2), 209-224.

Reinartz, W.–Haenlein, M.–Henseler, J. 2009. An Empirical Comparison of the Efficacy of Covariance-based and Variance-based SEM. *International Research in Marketing* 26(4), 332-344.

Steenkamp, J. E. M.–Baumgartner, H. 2000. On the Use of Structural Equation Models for Marketing Modeling. *International Journal of Research in Marketing* 17(2-3), 195-202.

Temme, D.–Hildebrant, L. 2006. *Formative Measurement Models in Covariance Structure Analysis: Specification and Identification Model*. SFB 649 Economic Risk Discussion Paper. Berlin: Humboldt University.

Vázquez, R.–del Rio, A. B.–Iglesias, V. 2002. Consumer-based Brand Equity: Development and Validation of a Measurement Instrument. *Journal of Marketing Management* 18(1-2), 27-48.

Wilson, B.–Callaghan, W.–Stainforth, G. 2007. An Application of Vanishing TETRAD Analysis to a Brand. *International Review of Business Research Papers* 3(2), 456-485.

Yoo, B.–Donthu, N. 2000. Developing and validating a multidimensional consumer-based brand equity scale. *Journal of Business Research* 52(1), 1-14.