
*Electronic Journal of Applied Statistical Analysis*
EJASA (2012), Electron. J. App. Stat. Anal., Vol. 5, Issue 3, 452 – 457
e-ISSN 2070-5948, DOI 10.1285/i20705948v5n3p452


# FORMATIVE AND REFLECTIVE MODELS: STATE OF THE ART

**Anna Simonetto**[*]

*Department of Economics and Management, University of Brescia, Italy*

Received 29 July 2012; Accepted 13 November 2012
Available online 16 November 2012

***Abstract***: *Although the dispute between formative models and reflective models is not exactly recent, it is still alive in current literature, largely in the context of structural equation models. There are many aspects of SEM that should be considered in deciding on the right approach to the data. This work is intended to be a brief presentation of the state of the art for SEM based on covariance matrices. We outline the different positions on five particular issues: causality, selection of observed measures, internal consistency, identifiability, and measurement error.*

***Keywords***: *Formative model, reflective models, structural equation models, causality, indicators.*

## 1. Introduction

Since the 1990s, the debate on structural equation models (SEM) has extensively increased. This extremely broad family of models allows analysis of different types of observed variables in order to identify one (or more) underlying latent variable or simply to represent concisely the phenomenon under examination. The literature is so rich, that it makes it difficult to approach SEM for the first time. We will focus on models based on the covariance matrix (CB-SEM), though many of the considerations also apply to the approach based on partial least squares (PLS-SEM) [6, 11, 19]. The CB-SEM approach (for synthesis henceforth only SEM) minimizes the difference between the theoretical covariance matrix and the estimated one. This is the approach used by many commercial software applications (e.g., LISREL and Mplus). The PLS-SEM approach is based on the maximization of the variance of the dependent latent variable.
In the following pages we will outline some of the main ideas offered in the literature on a particular theme: the contrast between formative and reflective models [2, 4, 7]. We can talk about a reflective model when the latent variable is the cause of the observed measures. Though

[*] E-mail: simonett@eco.unibs.it

the construct is not directly measurable, it exists independently of its effect indicators. For example, intelligence determines the responses of a subject to a questionnaire designed to assess this aspect, not vice versa. There are some aspects, however, that we cannot consider as latent constructs existing a priori: they are determined by the observed measures, which become the causes of the latent variables [10]. In these cases, the correct model is the formative one: the phenomenon is defined by, or is a function of, the observed variables. For example, the socioeconomic status (SES) is determined by several factors (salary, home ownership, educational and professional prestige). To achieve a new level of education likely increases the status without directly affecting the remaining causes. The observed variables are called causal or composite indicators, and the model could be called index model.

Recently, Edwards [9] showed some concerns about the use of formative models: "The presumed viability of formative measurement is a fallacy, and the objectives of formative measurement can be achieved using alternative models with reflective measures." We will explore his concerns in the sections that follow.

### *1.1 Formalization*

Let $Y_i$ be the *i*-th standardized observed variable, $X_i$ be the *i*-th standardized observed variable and $\eta_j$ be the *j*-th standardized latent variable. The direct reflective model (Figure 1-a) specifies the direct effects of a construct on its measure:

$$Y_i = \lambda_{ji}\eta_j + \varepsilon_i \tag{1}$$

where $\lambda_{ji}$ is the expected effect of $\eta_j$ on $Y_i$ and $\varepsilon_i$ is the measurement error associated with $Y_i$. We will consider $\varepsilon_i$ uncorrelated with $\eta_j$, $Cov(\varepsilon_i, \varepsilon_l) = 0$ for $i \neq l$, and finally, $E(\varepsilon_i) = 0$.

Figure 1-b represents the direct formative model in which composite indicators are related causes of the phenomenon of interest (index):

$$\eta_j = \sum_{i=1}^{q} \gamma_{ij} X_i + \zeta_j \tag{2}$$

where $\gamma_{ij}$ expresses the contribution of the *i*-th observed variable to the *j*-th construct, and $\zeta_j$ is the measurement error associated with $\eta_j$. We consider $Cov(X_i, \zeta_j) = 0$ for $\forall i$ and $E(\zeta_j) = 0$.

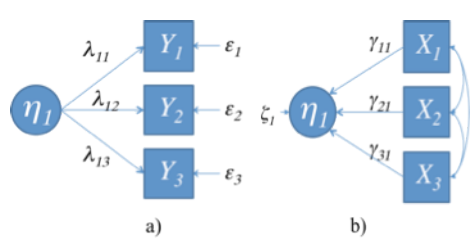


**Figure 1. a) reflective model; b) formative model [10].**

## 2. Reflective construct or composite index

As we have seen, one of the crucial aspects in the two approaches is the causal link between observed measures and latent construct. Edwards and Bagozzi [10] indicate four conditions to

evaluate the causality: cause and effect must be distinct entities, there must be association between the cause and its consequence and a temporal precedence between them, and lastly, we need to eliminate every other possible reason that can explain the assumed relationship between cause and effect. The direction of causality defines which objects are the causes and which are their consequences, so that changes in the causes are reflected in changes in the consequences.
For formative models we usually find, in the literature, that changes in the manifest variables determine a composite index change. Fornell and Bookstein [12] prefer to talk about determination rather than causality: *"*Constructs are conceived as explanatory combinations of its indicators.*"* One of the concerns of Edwards [9] draws on these reflections. As we have seen, to talk about causality there must be two distinct objects (cause and consequence); in formative models this requirement seems to be less because the latent construct is composed by its measures and therefore cannot be a separate thing.
Unlike many authors who identify each construct as reflective or formative, regardless of the manifest variables considered, Wilcox et al. [18] suggest that it is not always possible to determine a priori whether a given construct is inherently reflective or formative. Often it is the structure of the observed measures that determines the nature of the construct: "One might also imagine that there could be procedures to measure constructs like SES reflectively - for example, through a series of questions like 'How high are you up the social ladder?'"[5].

## *2.1 Selection of observed measures*

For both approaches, the selection of the indicators related to the latent phenomenon under investigation is crucial. Theoretically, we should be able to identify all and only those aspects that best identify (as a cause or as a consequence) the latent phenomenon, but it is not easy to understand the impact of the addition or removal of an indicator with respect to the global definition of the construct. For reflective models, if we remove an indicator, the correlation of the remaining $Y_i$ with the latent variable and the correlation between the remaining indicators do not change (interchangeability of effects indicators). So as long as we maintain a sufficient number of indicators, the interpretation of the model does not change. With formative models, each observed indicator describes a specific aspect of $\xi_j$ ; redundant measures disrupt the process of model estimation so they have to be eliminated a priori. To remove one or more observed measures that conceptually are key factors in the latent construct involves removing a specific aspect of the construct, so composite indicators are not interchangeable [10].

## *2.2 Internal consistency*

A SEM feature is the internal consistency: indicators positively associated with the same concept must be positively correlated to each other. For reflective models with standardized variables (1), $\lambda_{ji}$ is the correlation of $Y_i$ with $\eta_j$ : $Cor(Y_1,Y_2)=\lambda_{11}\lambda_{12}$. If $Y_1$ and $Y_2$ have a positive association with $\eta_j$, then even $Cor(Y_1,Y_2)$ is certainly positive and increases with the increase of $\lambda_{ji}$. For the formative model (2), it is not possible to know in advance the correlation between any pair of composite indicators: observed variables referring to the same concept may have a positive or negative correlation, or they could also be uncorrelated because they must represent different aspects of the construct. As their correlations increase, $\gamma_{ij}$ s become unstable with large standard errors. With regard to the optimum correlation of indicators, in the reflective model low correlation between constructs corresponds to low reliability of the found measure, as least one of them is not highly correlated with the latent variable under study. With the formative model we can observe that, if composite indicators are strongly correlated with each other, it is difficult to distinguish the impact that each observed variable $X_i$ has on the construct $\eta_j$. Edwards [9] stresses, however, that a low internal consistency is not automatically a symptom of a formative model. In addition, Wilcox et al. [12] disagree with the idea that the low correlation between observed measures is a necessary condition for the formative models. They argue that it is possible that causal indicators are strongly correlated, since the correlation is derived from exogenous components to the model considered, as response or single source bias (because a single individual fills out the entire questionnaire) and artifact (for example, integer scale).

### *2.3 Identifiability*

A model is identified if it is possible to obtain unique estimates for the involved parameters. It is one of the most critical aspects of structural equation models, since a priori it is not checked for any model. Criteria for formative PLS-SEM are very different and less restrictive [6]. To be identified, a CB-SEM must meet certain prerequisites that differ significantly between the two approaches. Since it is such an important issue, it has been particularly discussed in the literature. Reflective CB-SEM "requires a minimum number of indicators to ensure model identification because the sample covariance matrix must include at least as many non-redundant elements as the number of parameters to be estimated by the model" [1, 16]. Usually, the model is identified if it has at least three effect indicators, and we scaled the latent construct by fixing the variance of the formative latent variable to unity or by fixing a loading from an indicator to the construct or from the formative construct to a reflective endogenous latent variable [2].

The formative CB-SEM, if considered in the pure form of (2), is not identified. In order to estimate the model, it must be inserted into a larger model that incorporates the effects for the latent phenomenon [3]. Diamantopoulos et al. [8] summarize the most-used strategies in three possible solutions. The first one suggests consideration of at least two reflective indicators (Figure 2) for the latent formative construct: the new model is a multiple indicator multiple cause (MIMIC) [13]. The second idea is to add two reflectively measured constructs as outcome variables, and the third strategy is to add a single reflective indicator and a reflectively measured construct as an outcome variable. The inclusion of these effect indicators is, according to Edwards [9], a weakness of the formative model. The estimation of loadings linking the latent construct to its consequences $(\lambda_{ji})$ has an impact on the estimated loadings that link the latent construct to its causes $(\gamma_{ij})$. This is conceptually wrong, because the structure that binds the latent construct to its causal indicators should not be influenced by the measures that have been observed as its effects: changing the consequences of the construct should not change the impact of the causes on $\eta_j$. In the literature it is possible to find other solutions for the identification of formative models. Treiblmaier et al. [17] proposed a two-step strategy to approximate the formative latent variable through a common factor that can be included in any SEM.

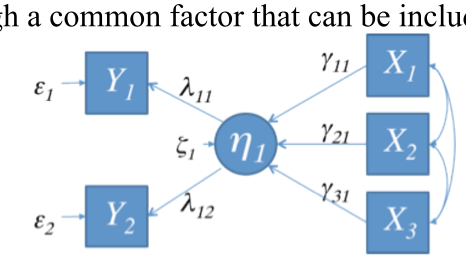


**Figure 2. Multiple indicator multiple cause model (MIMIC).**

### *2.4 Measurement error*

A fundamental aspect of SEM are measurement errors. In reflective models, we have measurement errors $(\varepsilon_i)$ at effect indicators level $(Y_i)$. In the pure formative models (2), we do not consider measurement error for the causal indicators $(X_i)$; we only consider the disturbance term $(\zeta_j)$, which is uncorrelated with $X_i$ [9]. The true variance in scores is greater than the variance of the observed values, while in reflective models the opposite occurs. At the base of the formative model, we have the hypothesis that the observed measures are free of measurement error, though in reality this occurs very infrequently (remember, for example, that the SEM had a very broad use in studies based on questionnaires). If real data violate this assumption, the formative model, in its most restrictive formulation (2), does not comply with one of the major strengths of SEM models, i.e., the processing of data affected by measurement errors [9].

### *2.5 Misspecification effect*

So far we have discussed the elements that make it possible to distinguish between a formative approach and a reflective one, as well as the distinctive features of each model. Now, we will discuss the effects of a model misspecification: a latent construct that has reflective measures is, indeed, modeled as formative (or vice versa). There are many studies that analyze the impact of misspecification error on the basis of various models [14, 15]. When we have a misspecified SEM, "serious consequences for the theoretical conclusions drawn from the model" exist [14]. In more detail, MacKenzie et al. [15] show the impact of this type of error on the parameter estimation. The loadings coming from a misspecified reflective latent variable are inflated (called the Type I error), while the loadings binding a formative latent variable to its indicators are deflated (called the Type II error). Avoiding errors of misclassification is crucial to avoiding drawing erroneous conclusions from empirical analyses.

## 3. Conclusion

The debate over the reflective or formative approach is still open. In the literature it is possible to find considerations on this theme also conflicting with each other. Looking at application studies, the CB-SEM reflective approach is widespread, while in the case of formative models, authors generally preferred to use PLS-SEM models. In the previous sections, we highlighted the main points that are necessary to assess whenever developing an analysis based on SEM: causality, selection of observed measures, internal consistency, identifiability, and measurement error. It is interesting to note that it is not possible to define strict rules of choosing between a reflective or a formative model. The choice must necessarily fall on the researcher, who must jointly consider the latent construct of interest and the measures (observable or observed) at his or her disposal.

## References

[1]. 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.

[2]. Bollen, K. (1989). *Structural Equations with Latent Variables*. New York: John Wiley.

[3]. Bollen, K. A., Davis W. R. (2009). Causal Indicator Models: Identification, Estimation, and Testing. *Structural Equation Modeling: A Multidisciplinary Journal*, 16, 498–522.

[4]. Bollen, K., Lennox, R. (1991). Conventional wisdom on measurement: A structural equation perspective. *Psychological Bulletin*, 100, 305-314.

[5]. Borsboom, D.; Mellenbergh, G.J.; van Heerden, J. (2004). The Concept of Validity. *Psychological Review*, 111:4, 1061-1071.

[6]. Ciavolino, E., Nitti, M. (2012). Using the Hybrid Two-Step estimation approach for the identification of second-order latent variable models. *Journal of Applied Statistics*. DOI:10.1080/02664763.2012.745837

[7]. Diamantopoulos, A., Siguaw, J.A. (2006). Formative versus reflective indicators in organizational measure development: A comparison and empirical illustration. *British Journal of Management*, 17, 263-282.

[8]. Diamantopoulos, A., Riefler, P., Roth, K. P. (2008). Advancing formative measurement models. *Journal of Business Research*, 61, 1203–1218.

[9]. Edwards, J.R. (2011). The fallacy of formative measurement. *Organizational Research Methods*, 14:2, 370-388.

[10]. Edwards, J. R., Bagozzi, R. P. (2000). On the nature and direction of the relationship between constructs and measures. *Psychological Methods*, 5, 155-174.

[11]. Esposito Vinzi, V., Chin, W., Henseler, J.,Wang H. (2010). *Handbook of Partial Least Squares - Concepts, Methods and Applications*. Berlin: Springer.

[12]. Fornell, C., Bookstein, F. (1982). Two Structural Equation Models: LISREL and PLS Applied to Consumer Exit-Voice Theory. *Journal of Marketing Research*, 19, 440-452.

[13]. Hauser, R.M., Goldberger, A.S. (1971). The Treatment of Unobservable Variables in Path Analysis. *Sociological Methodology*, 3:81-117.

[14]. 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.

[15]. MacKenzie, S.B., Podsakoff, P.M., Jarvis, C.B. (2005). The problem of measurement model misspecification in behavioral and organizational research and some recommended solutions. *Journal of Applied Psychology*, 90:4, 710-730.

[16]. Reinartz, W., 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.

[17]. Treiblmaier, H., Bentler, P., Mair, P. (2011). Formative Constructs Implemented via Common Factors. *Structural Equation Modeling*, 18:1, 1-17.

[18]. Wilcox, J.B., Howell, R. D., Breivik, E. (2008). Questions About Formative Measurement. *Journal of Business Research*, 61:12, 1229-1237.

[19]. Wold, H. (1975). Path models with latent variables: The NIPALS approach, in Quantitative sociology: *International perspectives on mathematical and statistical modeling*. H. M. Blalock, A. Aganbegian, F. M. Borodkin, R. Boudon and V. Capecchi, New York: Academic Press.