Cadogan & Lee's (2010) Suggestion for Measuring Endogenous Formative Variables: An Empirical Example.

In recent methodological articles related to structural equation modeling, the question of how to measure endogenous formative variables has been raised as an urgent, unresolved issue. This paper presents an empirical example from the CRM system development context to test Cadogan & Lee (2010)'s conceptual suggestion, which addresses this technical dilemma. PLS path modeling is used to demonstrate the feasibility of measuring antecedent relationships at the formative dimension level, not the formative construct level. The results indicate that Cadogan & Lee's (2010) suggestion is a useful approach to assessing structural equation models with endogenous formative constructs.

Keywords: Formative measures; Research methodology; Structural equation modeling
Track: Marketing Research and Research Methodology

1. Challenges with Formative Measures

Compared to reflective measurement models, the use of formative measures in empirical studies remains scarce (Diamantopoulos, Riefler & Roth 2008, 1203). The lack of popularity of formative measures in marketing research has arguably been influenced by the lack of practical guidelines how to create, estimate and validate formative models, in sharp contrast to standardized development procedures that have been developed for reflective measures over the years (Diamantopoulos et al. 2008, 1208). The choice of measurement perspective is still often ignored by researchers (Diamantopoulos 2006), despite increasing evidence in literature about the undesirable consequences of model misspecification (Jarvis, MacKenzie & Podsakoff 2003). In recent years, though, scholars have begun to challenge the "blind adherence" to the reflective approach with its strict emphasis on exploratory factor analysis and internal consistency (Coltman, Devinney, Midgley & Venaik 2008, 1251).

Structural models with formative measures pose a particular type of problem, which has remained largely unsolved to date. Diamantopoulos et al. (2008, 1216) voiced their concerns about "the conceptual plausibility of formatively-measured constructs occupying endogenous positions in structural models", and stressed the urgency of finding a solution to this dilemma. This is a challenge with endogenous formative constructs due to different nomological networks of antecedents and consequences (Jarvis et al. 2003). As a response, Cadogan & Lee (2010) demonstrated the inappropriateness of developing theory about antecedents to endogenous formative constructs at the aggregate level (i.e. path relationships between latent variables). Rather, antecedents' relationships to the dependent formative construct should be assessed at the formative dimension level (i.e. path relationships from latent variable to dimension), which would be unorthodox in structural equation modeling. *The purpose of this paper is to empirically test the feasibility of Cadogan & Lee's (2010) conceptual solution to the measurement of endogenous 2nd order formative constructs.*

2. Measuring Endogenous Formative Variables

As Cadogan & Lee's (2010) novel approach has been neither discussed nor tested in other published articles, the following discussion is based on their article unless stated otherwise. They identified two important issues, which provide support for assessing the relationships between antecedents and formative dimensions, not the formative construct. The first issue is related to the conceptual distinction between formative latent variable and formative composite variable. Theoretically, the relationship between antecedents and formative latent variable can be assessed at the formative construct level. However, a formative latent variable requires a census of all possible causes, which is usually empirically unrealistic. Thus, in most cases the construct is not a formative latent variable but in fact a formative composite variable. A formative composite variable is merely a collection, not a census of formative dimensions. In the case of a formative component variable, antecedents can be only assessed based on their correlations with the specific set of formative dimensions proposed to form the formative composite variable. Unfortunately, there is no generalizability in such results. Consequently, the solution is to assess relationships between antecedents and formative dimensions.

The second issue is related to the different nomological networks of formative dimensions' antecedents. In other words, formative dimensions may be influenced by common antecedents in different magnitudes, or they may have different antecedents altogether. Thus, examining the relationships from antecedents to a formative composite variable may conceal significant relationships or display non-existent relationships. As a result, empirical findings regarding antecedent relationships would be ambiguous at best. In a similar vein with the first issue, the solution is to assess relationships between antecedents and formative dimensions, not the formative composite variable.

Cadogan & Lee (2010, 7-8) further argued that any variation in a formative construct must occur either due to variation in one or more formative dimensions, and/or due to variation in unknown dimensions (error term). While this ambiguity is inherent to a formative latent variable, a formative composite variable allows parameters to be explicitly estimated in the absence of the error term (Diamantopoulos 2006). Thus, hypothesized antecedent relationships and dimension weights can only be empirically tested with a formative composite variable. On the other hand, results related to endogenous formative composite variables cannot be extended to endogenous formative latent variables, which cannot be tested empirically under any circumstances (Cadogan & Lee 2010, 9).

As the formative dimensions have an important role in assessing the relationships in the structural model, it is important to be able to estimate their measurement error. A type II 2nd order measurement model (Jarvis et al. 2003), namely, a 1st order reflective 2nd order formative model, does not suffer from this problem concerning the lack of estimation of item-level measurement error with formative constructs (Diamantopoulos 2006, 15). Estimating measurement error is more problematic with endogenous 1st order formative measures. Edwards & Bagozzi (2000) introduced a “spurious model” with multiple common causes, which represents a conceptual attempt to tackle the issue of measurement error estimation with formative measurement models. Latent variables are intentionally included to enable the estimation of measurement error at the indicator level. This is achieved by assigning each formative indicator a single reflective indicator of its respective latent variable. Its conceptual justification is questionable, though (Diamantopoulos 2006; Diamantopoulos et al. 2008).

In summary, the appropriate approach is to test antecedent-endogenous formative composite variable relationships at the formative dimension level of a type II 2nd order construct. According to Cadogan & Lee (2010), if the formative dimensions are logically formative, dimension level modeling is the most appropriate methodological approach. The conceptualization of an endogenous 2nd order formative composite variable with antecedent relationships measured at the formative dimension level (p. 31) is shown in Fig. 1.

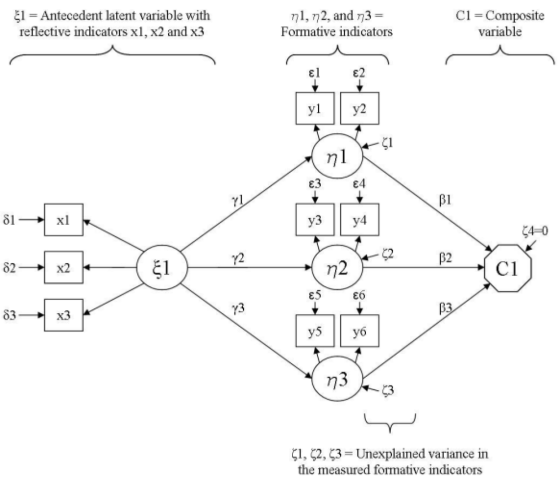

Figure 1. Endogenous 2nd order formative composite variable (Cadogan & Lee 2010)

In Fig. 1, C1 represents the endogenous formative composite variable (error term $\xi4=0$), which is shaped like a hexagon to distinguish it from a formative latent variable. The exogenous reflective antecedent variable ($\xi1$) with three indicators influences C1 only through reflective LVs $\eta1$, $\eta2$ and $\eta3$, which act as C1’s formative dimensions. Therefore, path coefficients (γ1-3) and measurement error (ξ1-3) are estimated at the formative dimension level.

Dimension weights (β1-3) represent the contributions of the formative dimensions to the composite variable. We test this solution with an empirical example from CRM development.

3. Empirical example: Research Model, Sample, and Measures

The research model in Fig. 2 conceptualizes the dimensions, antecedents and consequences of CRM system development. CRM system development is conceptualized as CRM delivery system (CRMDS), which is an application of an innovation delivery system (Leonard-Barton 1988) originated in the innovation diffusion theory literature.

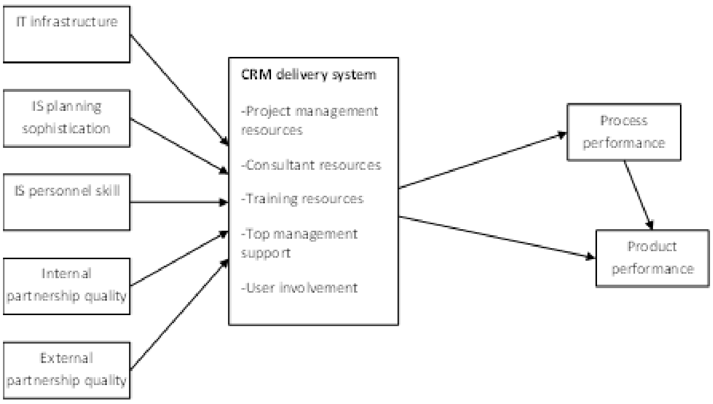

Figure 2. Research model

Karimi, Somers & Bhattacherjee (2007) introduced the ERP (enterprise resource planning) delivery system construct, which included project management resources (PMR), consultant resources (CR), training resources (TR) and top management support (TMS). Based on a review of marketing studies (e.g. Chen & Popovich 2003; Zablah, Bellenger & Johnston 2004), we added user involvement (UI) as a fifth dimension into a new concept CRM delivery system, which is a type II 2^{nd} order formative construct. As the dimensions were not identified through a census, they form a formative composite variable, not a formative latent variable. Following Jarvis et al. (2003), CRM delivery system is clearly formative in nature: its dimensions will not necessarily co-vary, the causality flows from the dimensions to the construct, and the dimensions are not interchangeable as the meaning of CRM delivery system would change. Consequently, the formative 2^{nd} order composite variable is a coherent description which depicts the multidimensional nature of CRM delivery system.

In this example, IT infrastructure (INF), IS planning sophistication (ISP), IS personnel skill (PS), internal partnership quality (IPQ), and external partnership quality (EPQ), are expected to be antecedents of CRM delivery system quality (Ravichandran & Lertwongsatien 2005). CRM delivery system is expected to influence the well-known IT project performance measures, namely, process performance (SPP) and product performance (SPD). Process performance is also expected to influence product performance (Wallace, Keil and Rai 2004).

The data set was collected from CRM client firms. The population sample consisted of 526 organizations. The final sample size after screening was 168 usable responses, which exceeded the minimum requirement for PLS-SEM (Barclay, Higgins & Thompson 1995).

Earlier studies (Karimi et al. 2007; Ravichandran & Lertwongsatien 2005; Wallace et al. 2004) have developed applicable reflective measures for all 1^{st} order constructs tested in the research model. The reflective measures met reliability and validity criteria (Table 1).

Table 1. Reliability and validity of reflective measures

LV	Items	SE	SD	Cr α	CR	AVE	INF	ISP	PS	IPQ	EPQ	PMR	CR	TR	TMS	UI	SPP	SPD
INF	4	,084	1,07	,81	,88	,64	**,80**											
ISP	2	,115	1,45	,80	,91	,83	,22	**,91**										
PS	2	,095	1,21	,85	,93	,87	,25	,31	**,93**									
IPQ	5	,085	1,08	,87	,90	,65	,29	,34	,37	**,81**								
EPQ	5	,088	1,12	,88	,92	,69	,29	,21	,23	,38	**,83**							
PMR	2	,101	1,28	,63	,83	,71	,27	,35	,23	,42	,23	**,84**						
CR	3	,106	1,35	,89	,93	,82	,22	,19	,11	,37	,27	,49	**,91**					
TR	3	,093	1,19	,79	,87	,70	,07	,19	,10	,27	,16	,39	,40	**,84**				
TMS	3	,112	1,42	,90	,94	,83	,16	,23	,22	,38	,11	,30	,26	,36	**,91**			
UI	3	,111	1,41	,88	,93	,81	,23	,13	,18	,32	,16	,46	,29	,31	,34	**,90**		
SPP	2	,132	1,68	,83	,92	,86	,10	,01	,08	,18	,16	,32	,29	,22	,17	,20	**,93**	
SPD	5	,098	1,24	,91	,93	,73	,23	,14	,21	,39	,37	,49	,49	,42	,34	,45	,43	**,86**

√AVE in **bold**

The 1st order reflective, 2nd order formative CRM delivery system construct was assessed following the recommendations by Hair, Ringle & Sarstedt (2011) which provided strong support for the external validity of CRM delivery system (Table 2). The key outcome variable product performance (SPD) was added to carry out this test.

Table 2. Validity assessment of CRM delivery system (CRMDS)

	loading	**weight**	**t-value**	**SE**	**β**	**R²**
Construct validity						
CRMDS → SPD			14,71*	0,044	0,64	0,410
Dimension validity						
PMR → CRMDS	0,70	0,19	10,98*	0,017		
CR → CRMDS	0,72	0,35	9,87*	0,035		
TR → CRMDS	0,70	0,27	10,51*	0,026		
TMS → CRMDS	0,66	0,30	10,29*	0,029		
UI → CRMDS	0,71	0,33	10,99*	0,030		

* Significant at the 0.001 level (2-tailed)

4. Results and discussion

The primary criteria for structural model assessment in PLS are the explained variances of endogenous constructs (R^2), and the strength of standardized path coefficients (β) coupled with significance testing (t-values) (Hair et al. 2011). As Figure 3 illustrates, the antecedent relationships of formative composite variable CRMDS (in grey) were measured at formative dimension level (PMR, CR, TR, TMS, UI), which resulted in a total of 25 antecedent paths (only significant paths are shown). Antecedents IPQ and ISP had significant paths to CRMDS through its formative dimensions. Following the hierarchical component model technique (Wold 1982), the total explained variance in CRMDS ($R^2=0.272$) could also be calculated in the PLS path model by conceptualizing CRMDS as a 1st order construct representing all five project-level IT resources PMR, CR, TR, TMS and UI.

While the formative composite has an error term fixed at zero, measurement error could also be estimated at formative dimension level in a Type II higher-order construct such as CRMDS here. The parameters for the 1st order reflective measurement models, which represent the formative dimensions of the 2nd order formative construct, remained stable across various structural models. Formative dimension weights also displayed the same robust qualities.

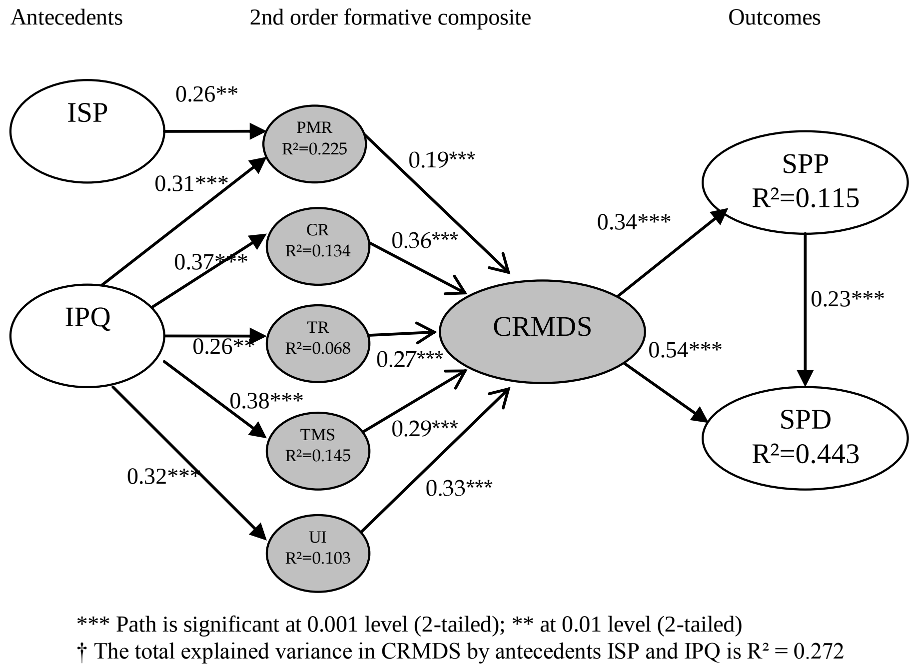

Figure 3. Results

Cadogan & Lee's (2010) suggestion proved to be useful in measuring simultaneously the antecedent relationships of each formative dimension, and their contribution to the formative construct as dimension weights. Formative dimension level analysis provides important information, which could not be measured at formative construct level. For example, the significant impact of ISP on PMR would have gone undetected. Similarly, the influence of IPQ on CRMDS through all its five dimensions would not have been discovered. Most importantly, though, this conceptualization allowed for the analysis of CRMDS in an endogenous position, which otherwise would have been theoretically untenable.

Cadogan & Lee's (2010) model is subject to the general limitations associated with formative measurement. Formative dimension weights vary across different empirical data sets and research contexts, leading to limitations regarding the generalizability of empirical findings (Bagozzi 2011). Reflective measures are thus considered more useful from a theory development perspective (Howell, Breivik & Wilcox 2007). Based on theoretical rationale, however, CRM delivery system is clearly a formative, multidimensional construct. Under these circumstances, Cadogan & Lee's (2010) suggestion is arguably the most useful approach to investigate formative variables, Type II in particular, occupying endogenous positions in structural equation models. In order to improve the generalizability of formative composite variables, future studies could also test them with predetermined dimension weights. These weights could be predetermined as equal weightings (Cadogan & Lee 2010), or based on theoretical considerations (Howell et al. 2007).

In conclusion, it is important to find a technical solution to measure antecedent relationships of higher-order formative constructs. When theoretically justifiable, a higher-order construct can more parsimoniously explain the single cumulative effect, as opposed to multiple distinct effects of individual facets, on outcome measures. In this particular empirical example, CRM delivery system incorporates the multidimensional phenomenon of CRM system development from five separate constructs into a single construct. If the measurement problems related to antecedent relationships of formative constructs can be addressed, the application of formative measures in empirical studies could improve the measurement model misspecification issues reported in marketing (Jarvis et al. 2003). Measurement model choice is a crucial methodological decision, which can gravely compromise the empirical results of any given study. The lack of a technical solution should not dictate an issue of such importance. There are certainly many marketing concepts for which formative measurement model specification is theoretically justified.

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