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Robustness Testing of PLS, LISREL, EQS and ANN-based SEM for Measuring Customer Satisfaction

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ABSTRACT Researchers have shown the Customer Satisfaction Index (CSI) can serve as a predictor for companies' profitability and market value. To measure a CSI model, we have to use a Structure Equation Model (SEM) technique. There are two types of SEM techniques – covariance-based (e.g. LISREL, EQS or AMOS) and component-based SEM techniques (e.g. Partial Least Square). With the growing importance of a CSI model, we must determine which SEM technique can better measure a CSI model. In addition, with the increasing complexity of a theoretical model (e.g. non-linear relations between variables), researchers have called for new SEM techniques that could address this issue. Hackle & Westlund (2000) contended that the Artificial Neural Network (ANN)-based SEM technique could be superior to traditional SEM techniques because it can measure non-linear relations by using different activity functions and layers of hidden nodes. Thus, this study extends previous research in several directions. First, we conduct the robustness testing of both covariance-based (LISREL and EQS) and component-based (PLS) SEM techniques, not only on a simulated CSI-like model but also on a real-life CSI model. Second, we explore the feasibility of an ANN-based SEM technique.

KEY WORDS: LISREL, EQS, PLS, ANN, robustness

Introduction

In 1989, the Swedish Customer Satisfaction Barometer (SCSB) was introduced as a tool for companies to assess their efforts in achieving customer satisfaction (Fornell, 1992). The successful experience of the SCSB has inspired the creation of American Customer Satisfaction Index (ACSI) and European Customer Satisfaction Index (ECSI). Researchers have shown the customer satisfaction index (CSI) can serve as a predictor for companies' profitability (e.g. Anderson *et al.*, 1994, 1997; Eklof *et al.*, 1999) and market value (e.g. Eklof *et al.*, 1999; Ittner & Larcker, 1996). Specifically, Ittner & Larcker (1996) estimated

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that a one-unit change in ACSI is associated with a \$654 million increase in the market value of equality above and beyond the accounting-book value of assets and liabilities. As a result, CSI score can complement traditional economic measures to assess a company's most precious asset – its customers.

A CSI model consists of a set of latent variables (LVs) that depict the cause-and-effect relations between the antecedents and consequences of customer satisfaction. To measure a CSI model, we have to use a structure equation model (SEM) technique. There are two types of SEM techniques – covariance-based (e.g. LISREL, EQS or AMOS) and component-based SEM techniques (e.g. Partial Least Square). With the growing importance of a CSI model, we must determine which SEM technique can better measure a CSI model. Cassel *et al.* (2000) suggested two criteria for choosing a SEM technique for a CSI model, including (1) the SEM technique should determine the CSI score to make the comparison possible and (2) the SEM technique should exhibit good statistical properties – robustness.¹ Previous research has conducted the robustness testing of Partial Least Square (PLS) on a simulated CSI-like model (e.g. Cassel *et al.*, 1999, 2000). However, few studies have conducted the robustness testing of both covariance-based and component-based SEM techniques simultaneously on a CSI model.

With the increasing complexity of a theoretical model (e.g. non-linear relations between variables), researchers have called for new SEM techniques that could address this issue. Hackle & Westlund (2000) contended that the Artificial Neural Network (ANN)-based SEM technique could be superior to traditional SEM techniques because it can measure non-linear relations by using different activity functions and layers of hidden nodes, and it might improve structural equation estimation even if not all the assumptions of the model are satisfied. From the above discussion, this study extends previous research in several directions. First, we conduct the robustness testing of both covariance-based (LISREL and EQS) and component-based (PLS) SEM techniques not only on a simulated CSI-like but also on a real-life CSI model. Although previous research conducted the robustness testing only on a simulated model, we believe that the real-life scenario testing is also necessary, because a real-life scenario is more versatile and complicated. Second, we explore the feasibility of an ANN-based SEM technique.

The paper is organized as follows: the next section overviews the SEM concept, compares covariance-based and component-based SEM techniques and describes the ANN architecture for SEM. The section after presents the process and results of robustness testing on a CSI-like simulated model. The subsequent section describes the results from a real-life CSI model. Conclusions are presented in the final section.

Overview of the Structural Equation Model

SEM has been used in a variety of settings, including strategy management thought (Cool *et al.*, 1989; Simonin, 1999), customer satisfaction studies (Fornell, 1992; Fornell *et al.*, 1995) and intellectual capital (Bontis, 1998; Bontis *et al.*, 2000). SEM techniques have made it possible for researchers to examine theory and measures simultaneously (Fornell & Bookstein, 1982). That is, SEM techniques provide researchers with the flexibility to model relations among multiple endogenous and exogenous LVs, and simultaneously to construct the relations between LVs and manifest variables (MVs).² Figure 1 depicts a simple SEM, where MVs are represented as squares and LVs are drawn as circles. SEM may include two types of LVs – exogenous LVs (ξ) and

Figure 1. A simple SEM model

endogenous LVs (η). It consists of two kinds of linear relationships – inner relations and outer relations. Inner relations specify relations between LVs and outer relations describe relations between a LV and its associated MVs. Gefen *et al.* (2000) found that PLS, LISREL, EQS and AMOS are the most commonly used SEM techniques. LISREL, EQS and AMOS belong to the covariance-based SEM techniques while PLS belongs to the component-based SEM technique.

Covariance-based SEM Techniques

Covariance-based SEM techniques estimate path coefficients and loadings by minimizing the difference between observed and predicted variance–covariance matrices. The observed variance–covariance matrix is calculated by the covariance structure of the MVs. The most widely used procedure to estimate parameters is the maximum likelihood estimate (MLE), which requires the observed data to be distributed as a multivariate normal (Byrne, 1994; Joreskog & Sorbom, 1989).

Component-based SEM Techniques

PLS is a component-based SEM technique because it estimates parameters similar to the principal component with a multiple regression approach. Unlike the covariance-based SEM techniques, the familiarity with PLS is relatively low (Hulland, 1999). Thus, we illuminate its algorithms in the following sections.

Inner relations

The inner relations depict the relationships among LVs

$$\eta = B\eta + \Gamma\xi + \zeta \quad (1)$$

where η is a vector of the endogenous LVs, ξ is a vector of the exogenous LVs, ζ is a vector of residuals, and B and Γ are the path coefficient matrices. The reduced form of

equation (1) is:

$$\eta = (I - B)^{-1} \Gamma \xi + (I - B)^{-1} \zeta = B^* \xi + \zeta^* \quad (2)$$

where B^* represents the total effect of exogenous LVs. With the assumption of $E[\zeta^* | \xi] = 0$, conditional expectation of equation (2) is:

$$E[\eta | \xi] = (I - B)^{-1} \Gamma \xi = B^* \xi \quad (3)$$

Thus, the prediction $E[\eta | \xi] = \hat{\eta}$ obtained from equation (3) with the parameters substituted by its ordinary least squares (OLS) estimates, is consistent with minimal variance. Wold (1985) called the conditional linear expectation equation (3) ‘predictor specification.’

Outer relations

The relations between MVs and LVs are defined by outer relations. Two kinds of outer relations can be specified in PLS – reflective and formative relations. Reflective items represent the effects of the construct under study. Formative measures are items that cause the construct under study.

The PLS algorithm

The PLS algorithm iteratively generates the estimates of LV scores based on inner and outer relations. That is, each estimated LV score is determined based on inner and outer relations until the two relations converge. PLS is called *partial* least square because each approximation step minimizes a residual variance only in either inner or outer relations, given the last estimates of LV scores in either relation. Thus, the PLS method involves the approximation procedures of inner and outer relations. In the outer relation approximation scheme, the LV scores are derived as weighted values of the associated MVs. In terms of reflective MVs, the loadings from the LV to MVs are used as the weights. In terms of formative MVs, the multiple regression coefficients from MVs to LV are used as weights. The derived LV scores are sent into the inner relation approximation. In the inner relation approximation scheme, a LV score is approximated by the weighted aggregate of its neighbouring LV scores. Various weighting schemes have been designed, including centroid weighting, factor weighting and path weighting schemes. The inner and outer approximation schemes then continue until the parameter estimates converge.

The covariance-based SEM techniques differ from the component-based SEM techniques in the basic assumptions. A covariance-based SEM technique estimates parameters by reproducing a covariance matrix as closely as possible to the observed covariance matrix. A covariance-based SEM technique assumes a parametric model in which the distribution of data must require multivariate normal distribution. Covariance-based techniques can lose predictive accuracy because of the factor indeterminacy problem. As a result, a covariance-based SEM technique is mainly for theoretical testing in which parameter estimations are the main concern. Specifically, in situations where prior theory is strong, covariance-based SEM techniques are more appropriate for measuring a SEM (Fornell, 1982). In contrast to the covariance-based SEM techniques, a component-based SEM technique aims to minimize errors in all endogenous LVs. It operates

as a series of interdependent OLS regressions, presuming no distributional form at all (Fornell & Bookstein, 1982). Because a component-based SEM technique estimates LVs as the linear combination of MVs, it can avoid the factor indeterminacy problem and inadmissible solution (e.g. not convergence or improper solution) problem. Besides, the derived LV score can be used for prediction. Thus, research suggested that the component-based SEM technique is primarily for predictive analysis in situations of high complexity but low theoretical information (Fornell, 1982).

In general, a covariance-based SEM technique requires a relatively larger sample than a component-based SEM technique. Besides, a component-based SEM technique can have both formative and reflective outer relations, while the covariance-based SEM techniques can have only reflective relations. Chin (1998) suggested that it is theoretically possible to use formative relations in the covariance-based SEM techniques, but it may have a variety of problems (e.g. identification problems). However, the advantages of a component-based SEM technique (e.g. small sample size, less requirement to sample distribution and fewer convergence problems) come with price. First, direct statistical tests are not available. Inference is only made possible by using jack-knife or bootstrapping procedures. Second, the results of a component-based SEM technique are often biased. Usually, the loadings are overestimated and the path coefficients are underestimated (Chin *et al.*, 1996). The effects of biased estimations can be reduced by increasing the sample size or by increasing the number of MVs associated with a LV. This property is called the consistency at large. We summarize previous discussions in Table 1.

ANN-based SEM Technique

Few studies have tried to design an ANN-based SEM, except for Hackl & Westlund (2000). Although their ANN architecture is intuitive and easy to implement, the proposed architecture cannot measure a complicated SEM, such as a CSI model. To address this issue, we propose a novel ANN architecture to estimate a SEM. In essence, the approximation procedure is very similar to PLS, except that the ANN-based SEM technique can simultaneously measure inner and outer relations.

Table 1. Comparisons of covariance-based and component-based SEM technique

Feature	Covariance-based approach	Component-based technique
Distributional assumptions	Multivariate normal distribution	None
Purpose	Theory oriented	Prediction oriented
Parameter estimates	Consistent	Consistency at large
Hypothesis testing	Available	Inference requires jackknife or bootstrapping
Sample requirement	Large	Small
Parameter identification problems	Not convergence or improper solutions	Few
LV scores	Factor indeterminacy	Explicitly estimated
Reflective and formative relations	Only reflective relations	Both

ANN is biologically inspired. It is composed of simple processing units (PEs, or nodes) and a set of connections between them. The connection between PEs is called weights, which determines how one PE affects the other PE. A subset of the PEs acts as input nodes and another subset acts as output nodes, which perform summation and thresholding. In this study, we employ a classic feed-forward neural network trained with the back-propagation algorithm to implement the SEM technique. A feed-forward neural network has a forward pass and a backward pass. The forward pass involves presenting a sample input to the network and letting activations flow until they reach the output layer. The linear sum, sigmoid function and Gaussian function are three often used activation functions. During the backward pass, the network's actual output (from the forward pass) is compared with the target output and the error estimates are computed for each output PE. The weights connected to the output PEs can then be adjusted accordingly to reduce errors. Parallel to the PLS algorithm, the ANN-based SEM has two approximation steps.

Outer relation approximation

The outer relation is estimated using an Observation-LV Network (OLN), shown in Figure 2. In this example, it is a three-layer network with three input nodes, one hidden node and three output nodes. The activation function used in the hidden node is a linear function. The purpose of the OLN is to derive LV scores to feed into the inner relation approximation. In Figure 2, y_i nodes represent the MVs of the associated LV η and $\hat{y}_i$ nodes are the estimates of y_i . A set of weights, dash lines with value -1 , are designed for minimizing the estimation error of the OLN. When the approximation converges, those weights on the left-hand side of η can be treated as weights for formative outer relations and those weights on the right-hand side of η can serve as loadings for formative outer relations.

Inner relation approximation

To estimate inner relations, we construct a hierarchical ANN typology where at the first layer is OLN to derive the LV score and at the second layer is the inner relations specified by a sets of PEs (see Figure 3). The ANN typology for inner relations is used to find relationships between LVs. The stopping criteria for the hierarchical ANN are either the result can achieve a low level of rooted mean square error (RMSE) or at most 100,000 iterations. Most of the time, we can have a low RMSE. That is, the architecture is quite stable. The proposed ANN-based SEM technique is a component-based technique.

Figure 2. An example of OLN

Figure 3. A hierarchical ANN topology for SEM

The Simulation Study

Data Generating Process

Because the covariance-based SEM techniques can estimate only reflective outer relations, we design a simulated CSI-like model with reflective relations to test the robustness of four SEM techniques. The data are generated according to a simplified CSI model (see Figure 4), which consists of three exogenous LVs ξ_1 , ξ_2 and ξ_3 and three endogenous LVs η_1 , η_2 and η_3 .

The inner relation is defined as

$$\begin{bmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \end{bmatrix} = \begin{bmatrix} \tau_{11} & \tau_{12} & \tau_{13} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \xi_1 \\ \xi_2 \\ \xi_3 \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 \\ \beta_{21} & 0 & 0 \\ \beta_{31} & \beta_{32} & 0 \end{bmatrix} \begin{bmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \end{bmatrix} + \begin{bmatrix} v_1 \\ v_2 \\ v_3 \end{bmatrix} \quad (4)$$

The MVs are denoted by x for ξ and y for η . The outer relations for ξ_i , $i = 1, 2, 3$

$$\begin{bmatrix} x_{i1} \\ x_{i2} \\ x_{i3} \end{bmatrix} = \begin{bmatrix} \lambda_{xi1} \\ \lambda_{xi2} \\ \lambda_{xi3} \end{bmatrix} [\xi_i] + \begin{bmatrix} \delta_{i1} \\ \delta_{i2} \\ \delta_{i3} \end{bmatrix} \quad (5)$$

Figure 4. The simulated model

For $\eta_i, i = 1, 2, 3$

$$\begin{bmatrix} y_{i1} \\ y_{i2} \\ y_{i3} \\ y_{i4} \end{bmatrix} = \begin{bmatrix} \lambda_{yi1} \\ \lambda_{yi2} \\ \lambda_{yi3} \\ \lambda_{yi4} \end{bmatrix} [\xi_i] + \begin{bmatrix} \varepsilon_{i1} \\ \varepsilon_{i2} \\ \varepsilon_{i3} \\ \varepsilon_{i4} \end{bmatrix}$$

(6)

In Figure 4, x_i and y_i can be determined by LVs ξ and random errors v , δ and ε . For the base model, the LVs ξ are generated from the symmetric beta-distribution $1.5 \times \beta(6,6)$. All λ_{xij} were set to 1/3, 1/3 and 1/3 for $i = 1, 2, 3, j = 1, 2, 3$, respectively. The τ_{1i} were set to 0.7, 0.1 and 0.2 for $i = 1, 2, 3$; $\beta_{21} = 0.5$, $\beta_{31} = 0.8$ and $\beta_{32} = 0.3$. λ_{yij} were set to 1.1, 1.0, 0.9 and 0.8 for $i = 1, 2, 3, j = 1, \dots, 4$, respectively. The noise δ_i and ε_i were generated from continuous uniform distribution, and the noise v_i was generated from the normal distribution. All errors have expectation value zero and account for 30% of variance of the corresponding dependent variable. The MVs x and y were transformed into scores on a 10-point scale (from 1 to 10) to correspond to the scale used in the CSI model. The LV scores were transformed into scores on a 100-point scale. For each testing scenario, we generated 200 samples and ran 30 replicates. We used the four SEM techniques to obtain the estimated parameters and then averaged the obtained parameters to facilitate comparisons.

Simulation design

To conduct the robustness testing, we design five testing scenarios: (1) a base model scenario: MVs x and y were generated according to the data generating process described previously; (2) a small sample size scenario: we reduce the sample size to 50; (3) a skewness scenario: we set all LVs ξ to $1.5 \times \beta(9, 4)$. The skewness of LVs would lead to the skewness of MVs; (4) a negative inner relation scenario: a CSI model might contain a negative relation. To test this, we set $\beta_{32} = -0.3$; and (5) the consistency at a large scenario: we increase the number of MVs by one for each LV, so the number of MVs increases from 3 to 4 for each LV ξ , and from 4 to 5 for each LV η . Table 2 summarizes the scenario designs.

Table 2. Scenario designs

Scenario No.	Description	Main difference
1	A base model scenario	
2	A small sample size scenario	Sample size is 50
3	A skewness scenario	All ξ are generated according to $1.5 \times \text{Beta}(9,4)$
4	A negative inner relation scenario	$\beta_{32} = -0.3$
5	A consistency at large scenario	The number of MVs is increased by one

Results

Model fit assessment

There is no overall goodness-of-fit measure existing for both covariance-based and component-based SEM techniques, because in essence these techniques have different assumptions. Hulland (1999) suggested that even PLS can report goodness-of-fit statistics such as the NFI or GFI, but these statistics are meaningless because the purpose of PLS is not to minimize the difference between the observed and the reproduced covariance matrices. Thus, we only produce good-of-fit statistics (RMSE, GFI and CFI) for LISREL (see Table 3). In general, the acceptable range for RMSE is less than 0.05, and the estimated value for GFI and CFI should be larger than 0.9 (Bagozzi & Yi, 1988). Except for scenario 2, goodness-of-fit criteria are all met. That is, under insufficient sample, LISREL could not fit the model well.

Table 4 reports the R^2 of four SEM techniques. In general, R^2 values of component-based SEM (e.g. PLS and ANN) techniques are smaller than that of the covariance-based SEM techniques (e.g. LISREL and EQS). The results suggest that the component-based SEM techniques are less accountable for the endogenous LVs than the covariance-based SEM techniques. In terms of R^2 , we observed that LISREL is similar to EQS, while PLS is similar to the ANN-based SEM technique, indicating the proposed ANN-based SEM technique is a component-based technique.

Path coefficient comparisons

To compare the path coefficients of the four SEM techniques, we need to obtain the standardized path coefficients in each scenario.³ Table 5 summarizes the differences of path coefficients between the estimated and the real path coefficients. If the difference of the path coefficient is negative, this indicates the estimated path coefficient is smaller than the real path coefficient.

(1) Scenario 1 (a base model scenario)

The results of the path coefficient differences can be grouped based on the covariance-based or the component-based SEM techniques. The implementation of LISREL and EQS might be different; however, the experimental result showed that they achieve similar results. The result of the ANN-based SEM technique is similar to PLS. In terms of prediction accuracy, the covariance-based SEM techniques can achieve better prediction results than the component-based SEM techniques. Researchers suggested that the path coefficients in PLS tend to be downward biased (Chin, 1998; Dijkstra, 1983). In this testing

Table 3. Goodness-of-fit for LISREL

Scenario	RMR	GFI	CFI
1	0.046	0.919	0.995
2	0.100	0.735	0.941
3	0.049	0.918	0.993
4	0.049	0.922	0.994
5	0.050	0.895	0.996

Table 4. R^2 results for four SEM techniques

Model	PLS			ANN			LISREL			EQS		
	η_1	η_2	η_3	η_1	η_2	η_3	η_1	η_2	η_3	η_1	η_2	η_3
1	0.56	0.34	0.63	0.55	0.33	0.63	0.71	0.46	0.76	0.71	0.46	0.76
2	0.57	0.34	0.65	0.56	0.32	0.65	0.72	0.45	0.79	0.63	0.45	0.73
3	0.48	0.29	0.59	0.46	0.29	0.58	0.64	0.41	0.72	0.62	0.41	0.72
4	0.56	0.33	0.46	0.55	0.33	0.45	0.72	0.45	0.62	0.72	0.45	0.62
5	0.59	0.34	0.67	0.58	0.34	0.66	0.72	0.44	0.78	0.72	0.44	0.78

scenario, the component-based SEM techniques underestimated all path coefficients, except for β_{32} .

(2) Scenario 2 (a small sample size scenario)

The component-based SEM techniques are quite robust against the small sample size problem, because these techniques achieve similar deviations as they do in base model scenario. Conversely, the covariance-based SEM techniques are more sensitive to the

Table 5. Differences of the path coefficients

	τ_{11}	τ_{12}	τ_{13}	β_{21}	β_{31}	β_{32}
Scenario 1						
PLS	-0.086	-0.019	-0.052	-0.098	-0.086	0.027
ANN	-0.090	-0.029	-0.054	-0.114	-0.078	0.024
LISREL	0.008	-0.012	-0.019	0.000	-0.013	0.014
EQS	0.008	-0.013	-0.019	0.000	-0.014	0.014
Scenario 2						
PLS	-0.090	-0.016	-0.048	-0.104	-0.097	0.050
ANN	-0.086	-0.031	-0.052	-0.116	-0.085	0.045
LISREL	0.003	-0.025	-0.036	-0.017	-0.046	0.057
EQS	0.003	-0.015	-0.064	-0.017	-0.047	0.059
Scenario 3						
PLS	-0.123	-0.017	-0.026	-0.104	-0.090	0.017
ANN	-0.112	-0.018	-0.043	-0.111	-0.080	0.022
LISREL	-0.014	-0.014	-0.002	-0.005	-0.011	0.003
EQS	-0.014	-0.013	-0.009	-0.005	-0.011	0.002
Scenario 4						
PLS	-0.106	-0.001	-0.014	-0.102	-0.199	0.171
ANN	-0.098	-0.018	-0.031	-0.111	-0.195	0.167
LISREL	-0.004	0.003	0.015	-0.009	-0.001	0.026
EQS	-0.003	0.004	0.016	-0.010	-0.001	0.026
Scenario 5						
PLS	-0.064	-0.011	-0.025	-0.093	-0.062	0.027
ANN	-0.057	-0.013	-0.024	-0.083	-0.060	0.023
LISREL	0.018	0.002	-0.004	-0.014	0.005	0.014
EQS	0.017	0.002	-0.004	-0.015	0.005	0.014

small sample size problem, because deviations are larger than deviations in the base model scenario.

(3) *Scenario 3 (a skewness scenario)*

In terms of skewness, all the SEM techniques are quite robust. That is, when the skewness of data distribution is moderate and the theory behind the model is strong, all the SEM techniques can achieve good results.

(4) *Scenario 4 (a negative inner relation scenario)*

In terms of negative relations, all the SEM techniques can identify this negative path coefficient. Again, the results of the covariance-based SEM techniques are more accurate in estimating this negative path than the component-based SEM techniques.

(5) *Scenario 5 (a consistency at large scenario)*

We observed that with the increasing number of MVs, the component-based SEM techniques have smaller deviations compared with the deviations in the base model scenario. Thus, researchers have suggested that the component-based techniques have the property of consistency at large (Chin *et al.*, 1996; Fornell, 1982). To the contrary, the results of deviation changes are inconclusive for the covariance-based SEM techniques. The property of consistency at large is insignificant in the covariance-based SEM techniques.

Comparisons of the LV scores

Because the covariance-based SEM techniques cannot report the LV scores, we only compared the LV scores between PLS and the ANN-based SEM technique. In a CSI model, the derived LV scores are often used for prediction. For example, researchers have shown that the score of CSI can serve as a predictor for companies' profitability and market value. The scores of the LVs are transformed into a 0–100 scale through formula (7).

$$Score = \frac{\sum_{i=1}^h w_i \bar{x}_i - \sum_{i=1}^h w_i}{9 \sum_{i=1}^h w_i} \times 100 \quad (7)$$

where h is the number of MVs associated with a LV and w_i are the weights (Fornell *et al.*, 1996). Because the absolute LV scores have no managerial meaning in the simulated models, we report only score differences between PLS and the ANN-based SEM technique (see Table 6). We observed that in terms of exogenous LVs ξ_i , the score differences are small, while in terms of endogenous LVs η_i , the differences are relatively large; in particular, when the skewness exists (see scenario 3).

Real-life Scenario

Because the conclusions made from the simulation scenarios are limited by the simulation design, we therefore extend from a simulation scenario to a real-life CSI scenario. Based on ACSI (Fornell, 1992; Fornell & Cha, 1994) and ECSI (Gronholdt *et al.*, 2000;

Table 6. LV score differences between PLS and ANN

Scenario	ξ_1	ξ_2	ξ_3	η_1	η_2	η_3
1	0.00	0.04	0.01	1.77	1.07	1.58
2	0.01	- 0.06	- 0.06	1.98	1.52	1.93
3	- 0.01	0.01	0.00	2.28	1.69	2.45
4	0.01	0.00	0.00	1.51	1.16	1.27
5	0.01	0.01	0.00	1.67	1.12	1.46

Kristensen *et al.*, 2000; Martensen *et al.*, 2000), we proposed a CSI model for a retail banking in Taiwan. The ACSI and ECSI have strengths and weakness. The relative strength of the ACSI over ECSI is its ability to detect the efficacy of a firm’s complaint handling capabilities by including a customer complaint construct. However, researchers have found that the construct of customer expectation used in the ACSI has less impact in the model (e.g. Johnson *et al.*, 2001; Martensen *et al.*, 2000). Thus, they suggested using a corporate image (used in ECSI) to replace customer expectation. Accordingly, our CSI model incorporates the strengths of both models. Figure 5 graphically shows our model. The CSI model is built based on two well-established theories – the quality, satisfaction and performance (QSP) theory and Hirschman’s (1970) exit-voice theory. The CSI model measures the cause-and-effect relationship running from the antecedents of the customer satisfaction level (corporate image, perceived quality and perceived value) to its consequences (customer complaints and customer loyalty). The antecedents of the customer satisfaction level are the drivers that affect customer satisfaction, while the consequences of customer satisfaction are performance indicators.

Samples

We employed the stratified random sampling method to choose customers who still have transactions with the retail bank. Based on gender, residential area and monetary contribution to the bank, we divided customers into 20 stratum and then allocated samples to each stratum proportionally. Using the stratified random sampling method, we obtained a representative sample on important characteristics, including gender, residential area and

Figure 5. CSI model for Taiwan

Table 7. The R^2 of endogenous LVs

SEM technique	Perceived value	CSI	Customer complaint	Customer loyalty
PLS	0.38	0.61	0.05	0.41
ANN	0.38	0.62	0.00	0.33
LISREL	0.47	0.87	0.02	0.50
EQS	0.48	0.87	0.02	0.50

monetary contribution to the bank. Trained interviewers conducted telephone interviews on selected samples. The telephone interviews lasted on average 10 to 12 minutes. After deleting cases with ambiguous values, we obtained a final sample of 532 customers.

Results

Model fit assessment

Table 7 presents the R^2 values of endogenous LVs. It can be observed that, in general, the R^2 values of the component-based SEM techniques are smaller than that of the covariance-based SEM techniques. The result is consistent with our findings in the simulation scenarios.

Path coefficients

Fornell & Bookstein (1982) suggested that two problems often interfere with the covariance-based approach – improper solutions (i.e. solutions outside the admissible parameter space) and factor indeterminacy. The reasons for improper solutions are: (1) the theory is wrong; (2) the data are inaccurate; (3) the sample size is too small; or (4) covariance structure analysis is not appropriate for the analysis task (Fornell & Bookstein, 1982; Gerbing & Anderson, 1987). In our sample, both LISREL and EQS suffered improper solution problems. In LISREL, the variance of $\theta_e(8,8) = 1.22$ is unreasonably large, leading to a negative R^2 value in its corresponding construct. In EQS, it reported that it is ‘constrained at lower bound’, indicating that some solutions are improper. To fix this problem, we substituted $\theta_e(8,8) = 1.22$ for $\theta_e(8,8) = 0$ in LISREL. In EQS, it automatically adjusted some parameters to solve this problem. Table 8 reports the path coefficients of the four SEM techniques. We observed that the two covariance-based techniques have similar results and the other two component-based techniques achieve similar results. However, the

Table 8. Path coefficients of four SEM techniques

Approach	PQ*→Im	PQ→CSI	Im→PV	Im→L	PV→CSI	CSI→CC	CSI→L	CC→L
PLS	0.40	0.40	0.26	0.14	0.47	−0.22	0.44	−0.23
ANN	0.47	0.40	0.26	0.04	0.49	−0.00	0.53	−0.04
LISREL	0.51	0.22	0.46	0.14	0.80	−0.15	0.63	−0.06
EQS	0.51	0.23	0.46	0.14	0.80	−0.15	0.63	−0.06

*PQ denotes perceived quality; Im denotes corporate image; PV denotes perceived value; L denotes customer loyalty, and CC denotes customer complaint.

Table 9. Scores of LVs

	Perceived quality	Image	Perceived value	CSI	Customer complaint	Customer loyalty
PLS	74.22	71.61	59.61	65.94	52.13	60.26
ANN	74.46	72.08	58.87	64.30	49.70	62.63

differences of the path coefficients between PLS and the ANN-based SEM technique were larger than the differences in the simulation scenarios. Besides, in a real-life CSI model, the path coefficients obtained by the component-based SEM techniques are not necessarily lower than the covariance-based SEM techniques (e.g. PQ→CSI). In this case, it is not clear which set of estimates is closer to the true parameter values.

Table 9 reports LV scores derived from PLS and the ANN-based SEM technique. In terms of LV scores, both techniques achieve similar results.

Conclusion

This study attempts to explore which SEM technique is more suitable for measuring a CSI model. Researchers have suggested that two criteria are particularly important, including (1) the SEM technique should determine the CSI score to make the comparison possible and (2) the SEM technique should exhibit good statistical properties. The obtained LV scores (e.g. CSI score) can serve as uniform and comparable measurement systems that allow for benchmarking over time and across firms. Besides, having the accurate path coefficients helps answer questions, such as why customers are satisfied or dissatisfied and how to improve customer satisfaction in a CSI model. In terms of LV scores, the covariance-based SEM techniques suffer from the factor indeterminacy problem. As a result, if the purpose of the study is to derive LV scores, researchers can choose only the component-based SEM techniques. In addition, if the model contains reflective outer relations, the component-based SEM technique is more suitable to estimate parameters.

In terms of robustness, we found that all of the SEM techniques are quite robust against the skewness scenario and the negative path coefficient scenario. However, the covariance-based SEM techniques are sensitive to the small sample size problem. The property of consistency at large only exists in PLS and the ANN-based SEM technique. The results are consistent with previous studies. Cassel *et al.* (1999, 2000) showed that PLS are quite robust against different problems. Bacon (1999) concluded that covariance-based techniques are also robust against violations of statistical assumptions.

Overall, the covariance-based SEM techniques can more accurately estimate path coefficients than the component-based SEM techniques. Chin (1995) pointed out that even with distribution violation, the covariance-based SEM techniques can be quite robust and may possibly produce better estimates of the population parameters than PLS. Accordingly, if the purpose of the study is to derive accurate path coefficients, the covariance-based SEM techniques can often achieve better results. However, the covariance-based SEM techniques might suffer the improper solution problem, which is not an issue for

Figure 6. Flowchart of choosing the SEM technique

the component-based SEM techniques. Figure 6 depicts the flowchart for determining the SEM technique.

We also explored the feasibility of an ANN-based SEM technique. Whether in the simulated or in the real-life scenario, the results showed that the ANN-based SEM technique behaves similar to PLS. Future research could base on the proposed architecture to explore different ANN settings (e.g. different activation function or different topology) so that the whole development of the ANN techniques can be brought into the SEM field.

Notes

1. Robustness refers to a situation where good statistical properties are achieved even if not all the assumptions of the model are satisfied (Cassel *et al.*, 2000).
2. A LV is a hypothesized and unobserved concept that can only be approximated by MVs.
3. We can obtain the standardized the path coefficients by multiplying the original path coefficient by the ratio of the standard deviations for the adjacent LVs.

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