Estimation of the European customer satisfaction index: Maximum likelihood versus partial least squares. Application to postal services

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Purpose:
To advocate the use of the maximum likelihood (ML) approach instead of the partial least squares (PLS) method for estimating customer satisfaction indices (CSI) models.

Summary:
Organizations are investing in research for developing accurate ways of assessing customer satisfaction (CS). PLS has been preferred to estimate the CSI models since their inception over the ML method. This choice, the authors contend, is based upon some misconceptions regarding the use of ML and ignores the recent advances in estimation methods that are robust to nonnormality and missing data.

In this study, a comparison of the ML and PLS approaches was made by evaluating perceptions of the Isle of Man Post Office products and customer service using a CSI format. Although both methods were robust, the ML approach was found to be advantageous. While PLS estimates were biased, ML provided unbiased estimates, more efficient treatment of missing data and formal tests for omitted parameters.

The authors suggest using PLS only in soft modeling situations, such as small sample sizes, weak theory, and large number of variables, which differ from the CSI research practice. (85 refs.)

Results:
In today’s competitive market, CS and customer retention are key issues to organizations. A number of national indicators reflecting consumer satisfaction across a wide range of organizations have been developed during the last decade. The CSI is a nationwide gauge of the extent to which companies and industries in general satisfy their customers.

The CSI model consists of a number of latent factors, each of which is operationalized by multiple indicators, and hence, it is a particular case of a structural equation model (SEM).
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The recommendation to use PLS-SEM (in brief PLS) (Ref. 1) was grounded on the argument that ML-SEM (in brief ML), software known as LISREL, makes strict assumptions about normality of the data.

ML assumes that observations are independent and follow a multivariate normal distribution. PLS uses nonparametric inference methods, such as jackknifing, and is free of these assumptions.

The paper is organized on the following lines:

- Description of data and questionnaire.
- Discussion of seven alternative SEM estimation procedures.
- Use of a confirmatory factor analysis to validate the questionnaire.
- Estimation using the seven procedures and comparison of results.
- Estimation of the causal relationships between dimensions in the European CSI model using the best of the methods.
- Interpretation of results and discussion of the methodological implications.

Method

The survey instrument was evolved by referring to questionnaire formats of European CSI, American CSI, etc., and a pilot survey. The final questionnaire contained 28 questions (observed variables) pertaining to the global CSI and referred to the latent variables:

- Quality of products (hardware) - QUAL 1.
- Quality of customer service (humanware) - QUAL 2.
- Perceived value.
- Image.
- Customer satisfaction.
- Customer loyalty.
- Customer complaints.

The questions are rated on a 1 to 10 scale. About 280 completed questionnaires from the Isle of Man residential sample of 1000 were collected during 2001 using a postal data collection mode.

Missing data treatment and estimation

The following seven methods were used:

1. Direct robust ML estimation.
2. Direct standard ML assumption.
3. Robust ML on a complete case.
4. Standard ML on the above.
5. Robust ML on a complete case.
7. PLS on the mean substitution.

A confirmatory factor analysis is an indicator of the underlying factor deleting one question of the image and another question that required the image factor. This could be ML, but would have been much more.

The results of the final CFA run methods. Procedures that are rejection of a model's constraints on goodness of fit measures and no.

The goodness of fit of the model's validity. The constraints that are in the absence of loadings on more covariances reveal the invalidity and fit indices are not available to measures.

The covariances obtained are:

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The customer satisfaction index was dropped from the model due to very few complaints, and one question in QUAL 1 was removed because of its low correlation with other items in QUAL 1. Computation of Mahalanobis distance to the mean vector resulted in removing four outlier observations.

Many variables showed evidence of moderate to severe nonnormality, as revealed by skewness and kurtosis values. Six variables and cases with more than 25% of data were deleted prior to estimation. The effective sample size was 258, and the average missing cases per variable was 11.

**Missing data treatment and estimation procedures**

The following seven methods were applied:

1. Direct robust ML estimation assuming the data are missing at random.
2. Direct standard ML assuming normality of data and missing at random.
3. Robust ML on a complete data set obtained by 'hot deck' imputation.
5. Robust ML on a complete data set obtained by mean substitution.
7. PLS on the mean substituted data set.

A confirmatory factor analysis (CFA) model fit to assess the quality of the indicators of the underlying factors and to locate invalid items, resulted in deleting one question of the image factor with the largest error variance and another question that required the addition of a significant loading parameter on the image factor. This could be detected in a straightforward manner in ML, but would have been much harder to detect had PLS been used.

The results of the final CFA model are compared for the seven estimation methods. Procedures that are not robust to nonnormality have led to the rejection of a model’s constraints. The model appears acceptable from the goodness of fit measures and more so when robust methods are used.

The goodness of fit of the model can be interpreted in terms of measurement validity. The constraints that are tested by fit indices in a CFA model are the absence of loadings on more than one factor, and the absence of error covariances reveal the invalidity of the items involved. The goodness of fit tests and fit indices are not available for PLS which focuses only on predictive fit measures.

The covariances obtained are very similar under hot deck imputation or direct
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ML with missing data, but are biased for mean imputation. The robust standard errors are similar across missing value treatments.

For this dataset containing only a small amount of missing data, but severely nonnormal, the use of an impression method and an estimation method with robust standard errors and test statistics appears to be a wise option.

A comparison of PLS and ML results using the same data, the mean imputed data and tests robust nonnormality, shows that loadings are systematically higher for PLS. This implies that PLS can result in retaining items with low convergent validity. Factor correlations and error variances are systematically lower for PLS showing bias. The differences between ML and PLS are greater than between any pair of ML methods.

The CFA model was reparameterized into a complete SEM specifying regression equations among factors. Robust direct ML estimation with missing data was used. In the resultant model, the main and only driver of consumer satisfaction is the quality of the post office products. Image and satisfaction are important factors in determining customer loyalty. Also, there is a significant effect of product quality on value.

To summarize, the advantages of ML over PLS include unbiased estimates, more efficient missing data treatments and formal tests for omitted parameters.

References:

Abstract:
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Software inspections

Applying sample

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The Journal of System

Purpose:
This paper investigates the software development process.

Summary:
The proposed sample driven inspection and resource scheduling process. In SDI, sampling process that contains most documents in order to utilize the results and future results.

This article describes the simulation and its appropriateness. Carlo simulation, and the sample driven inspection case study using the robustness to sample representation simulation using a capture-re-
fish of the results and future results.

Results:
SDI consists of pre-inspection estimate which documents are needed for different types of inspection conducted on the

After a brief review of the paper introduces the concept of scheduling and main inspection

Sample driven inspections

The goal of the sampling document's quality with a number of types of documents are needed for different types of document can be sampled while for code or design