International Journal of Business Quantitative Economics and Applied Management Research

ISSN: 2349-5677

Volume 1, Issue 10, March 2015

The analysis of structural equation models by PLS method in research on inter-organizational relationships: the case of research in Logistics

Mohammed Amine BALAMBO
Professor at the FSJESK, University Ibn Tofail Kenitra (Morocco) / Research Associate at CRETLOG- Université Aix-Marseille (France)
Mail: balambo@gmail.com

Jamal EL BAZ
Professor at EST Agadir, University Ibn Zohr
Mail: j.elbaz@uiz.ac.ma

Sara LAZAAR
Phd Student, Ibn Tofaîl University (Morocco)
Mail: Saralazaar@gmail.com

ABSTRACT

Structural equation enjoyed great popularity in management science, especially in the literature on inter-organizational relationships. Indeed, this literature uses variables wanting measure attitudes partners (trust, commitment, ...) (Valletta Florence, 1988; Livolsi and Meschi, 2003). These correspond to latent variables that represent indirectly observable phenomena. This literature also tends to want to build models that claim to approach the complexity of real life situations, which leads them to build multivariate models and complex interactions. This has led researchers to use more structural equations to meet these needs. We demonstrate in this communication the interest of using the PLS approach in Research Logistics as an alternative to the use of LISREL approach, an emerging technique for the analysis of structural relationships that proves suitable for Research where the unit of analysis is the company, where the samples are not important.

Keywords: Structural Equations, Logistics, Methodology, Data Analysis, PLS.

Introduction

The quantitative literature in management science appealed to traditional statistical approaches to validate quantitative models. This was mainly the multiple regression analysis, discriminant analysis, or analysis of variance (Roussel et al. 2002). However, these analyzes have shown their limits quickly in a discipline that deals with complex phenomena, since they do not allow to assess comprehensively complex search models taking into account the measurement errors.

The methods of second generation called structural equation methods went beyond the limits of traditional approaches, allowing not only the evaluation and comparison globally complex search models by taking into account the measurement errors but also, as noted by Lacroux (2010), to test simultaneously the existence of causal relationships between several explanatory latent variables and several variables to explain. These methods also allow the construction and testing of the validity and reliability of latent constructs constructed from several indicators.

1. The methods of structural equation

The methods of structural equation had their infancy in the 60s, thanks to the work of Jöreskog (1966). These methods were originally designed to test multiple causal relationships. Gradually, the practice has expanded to cover other fields of analysis such as Confirmatory Factor analysis that analyze the validity of the latent constructs or the multi-group analyzes (El Akremi, 2005). These methods have revolutionized the field of statistical analysis they allow to satisfy conditions that no first generation method can not fulfill (Valette-Florence, 1988). These conditions are summarized by Fornell (1982) defends four conditions to belong to this generation methods: the ability to simultaneously process multiple sets of explanatory variables observed and explained, ability to analyze the links between unobservable theoretical variables and allow for errors at the measure and, finally, ability to confirmatory applications.

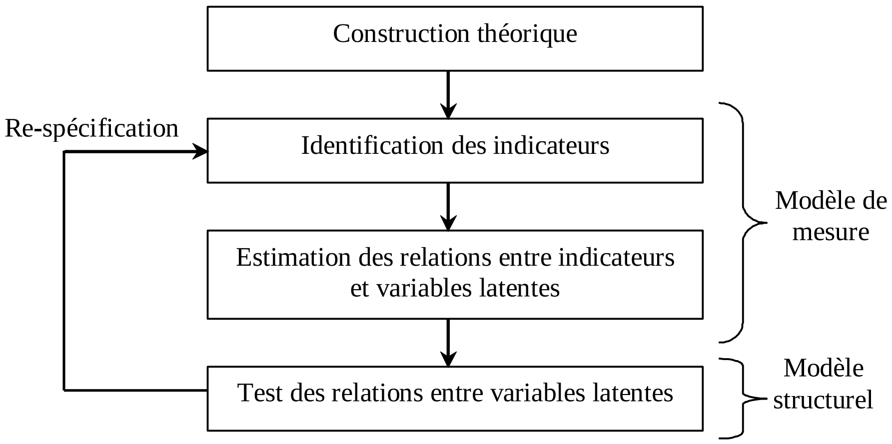
A structural equation these methods are associated analysis techniques. The most widely used technique in the literature in management science is that based on the analysis of covariance (covariance based structural equation modeling). She was the first to be used and be implemented in software, which was the result of collaboration between Jöreskog and Sörbom (1970), known as LISREL (LInear Structural relationships). The technique has been more and more improvements and other software have emerged always based on the analysis of covariance such as EQS Bentler (1980).

International Journal of Business Quantitative Economics and Applied Management Research
ISSN: 2349-5677
Volume 1, Issue 10, March 2015

A second emerging technique used in structural equation approaches is that based on the analysis of variances, known under the name of the PLS approach (Partial Ballast Square) which is adapted to certain structural models for which conventional estimation procedures may prove difficult to use (Lacroux 2010). This technique was proposed by Wold as a "soft modelisation" (Soft Modeling), and led to several software that LVPLS of Löhmoller (1984), PLS Graph Chin (1993), or software developed at the University of Hamburg called Smart PLS by Ringle et al. (2005).

The structural equation model is built to a deductive logic of theoretical demonstration and the subject of two kinds of specifications that the splitting into two parts as shown in the following figure.

Figure 1: The stages of the construction of the structural equation model



Source: (Meschi and Livolsi, 2003)

The structural equation model consists of two parts. A measurement model that refers to the identification and estimation of latent variables from the indicators and a structural model which refers to the determination of causal relationships between latent variables and allows to trace the sense assumptions component model research to test.

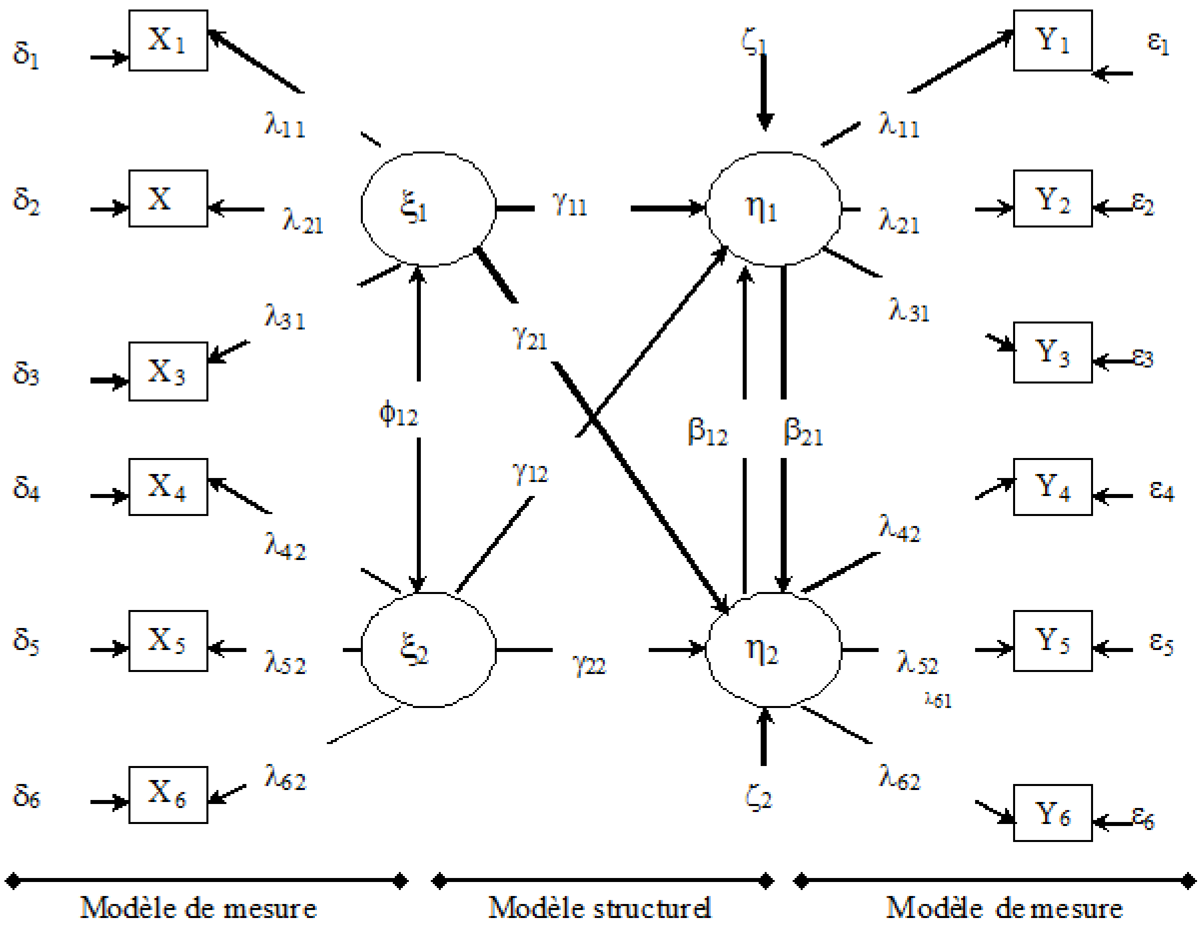
This scheme allows to distinguish between measurement model and structural model.

International Journal of Business Quantitative Economics and Applied Management Research

ISSN: 2349-5677

Volume 1, Issue 10, March 2015

Figure 2: Modelling of a structural equation model



Source: Aurifeille (1996)

Circles represent latent explanatory variables and explain and squares correspond to indicators to measure latent variables.

The measurement model consists of the set of relationships between indicators and the latent variables they measure. In this sense we distinguish two forms of contributions to the latent variable indicators. The built-called reflexive and formative constructs. We will treat these two concepts in the specification of structural equation models.

2. The specification of structural equation models

The specification of the measurement model is an important step in the process of using structural equation models. A latent variable is a variable that is not directly observable, and therefore requires passage through indicators or manifest variables that measure the variable.

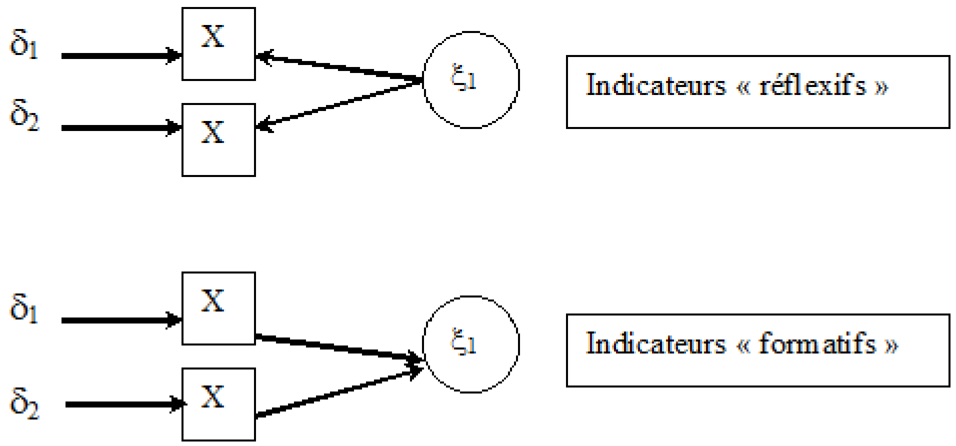
International Journal of Business Quantitative Economics and Applied Management Research
ISSN: 2349-5677
Volume 1, Issue 10, March 2015

The dominant paradigm in test theory was that represented by Churchil (1979), which considers the manifest variables are assumed to represent their latent variable. In this sense, it is postulated that all indicators are consistent in the way they measure the phenomenon, and allow all reflect the same variable. Consequently, the researcher must ensure that the significance of the latent variable constructed based on these indicators, to be significantly correlated. In this sense, a well-built latent variable is a variable whose change should be accompanied as closely as possible by the variation of all the indicators that compose it. This classical test theory then all variables considered as reflexive. Going through a purification step of items by various researchers to ensure internal consistency and validity of variables as a preliminary test demonstrates that consideration of reflexivity variables.

However, in some studies, it is possible to end up with some latent variables consist of a combination of indicators not necessarily correlated, since they measure different phenomena theoretically. These indicators are then used to form the latent variable. We'll talk then formative variables where the causality of these indicators will go towards built. A recurring example in management science is the measure of the overall performance, which can be composed of several indicators detailing financial performance and non-financial performance. All these indicators help to measure the overall performance, without assuming correlation between these indicators do not measure the same phenomenon.

The following diagram can distinguish between latent variables reflective and formative.

Figure 3: Specifying relationships between latent variables and their indicators



Source: (Meschi and Livolsi, 2003)

In the first type of specification indicators are a reflection of the latent variable where it remains the cause of the indicators, with each indicator is linked to the latent variable with a simple regression equation of the type:

In the second type of specification the latent variable is a reflection of all the indicators where it remains the cause of the latent variable. The model is then formalized by a multiple regression equation:

It is important for research to distinguish between reflective and formative constructs. Indeed, poor specification of the model decreases the quality of the measurement model and therefore the quality of the structural model (MacKenzie et al. 2005).

This distinction will result in different treatment at assessing the validity and reliability when it comes to a reflexive or formative variable. While conventional analysis of the validity and reliability approaches based on the assumption of the correlation between the indicators and therefore the search for dimensionality and homogeneity of indicators in the case of a reflexive latent variable, this may, in the case of a formative variable, eliminating an indicator that might make sense in the search.

3. The estimation methods of structural equation models: Differences between "LISREL method" and "PLS method"

There are mainly two major approaches aimed estimating structural equation models, the approach "LISREL" based on covariance analysis and approach "PLS" based on the analysis of variance. The estimate allows, based on different types of algorithms to network within the measurement model between the indicators and the latent variables on one hand, and to calculate the structural coefficients in the structural model on the other.

The LISREL method remains the most common technique in management science that is based on the maximum likelihood, and is based primarily on software developed by Jöreskog and Sörbom known LISREL. Then we find the second emerging methodology based on the analysis of variance maximizing the explanatory power of the indicators, based on an algorithm called Partial least square (PLS) (Lacroux 2010).

The distinction between PLS and LISREL method method was demonstrated by Chin (1995) cited by (Lacroux 2010) by analogy with the factor analysis. For him, the difference is the same as that between the classical factor analysis and principal component analysis. The principal component analysis does not take into account the measurement errors but always gives a solution. In this sense, unlike the LISREL approach or multiple regression, PLS approach avoids the unacceptable solutions and uncertainty factors (Fornell and Bookstein, 1982). PLS eliminates the uncertainty factor of the problem and provides an accurate definition of the component scores, using an iterative estimation technique.

International Journal of Business Quantitative Economics and Applied Management Research
ISSN: 2349-5677
Volume 1, Issue 10, March 2015

Lacroux (2010) makes an interesting comparison between the two approaches based on the work of (Jöreskog and Wold (1982), Chin (1995) Haenlein and Kaplan (2004) and Sosik et al. (2009), which allows to synthesize different characteristics and uses of LISREL and PLS approaches.

In this sense, many differences exist between the approach LISREL and PLS approach. As part of the LISREL approach, the researcher must fulfill the multinormality to be able to rely on maximum likelihood algorithms where all variables must be continuous or interval and normally distributed. While the PLS approach is suitable for nominal variables, interval or continuous and requires little statistical conditions on the variables of the model.

On the other hand, if the approach is well suited to LISREL models have been building a solid theoretical and based on measurement scales have already been tested earlier, the PLS approach is suitable for exploratory analyzes testing of partial models.

The requirements in the number of respondents have hampered the use of the method in structural equations in disciplines in management science where the unit of analysis is the company as is the case of logistics interested an inter organizational context. Indeed, the LISREL method requires large samples exceeding 200 observations (Roussel et al. 2002), or with a number of observations from 5 to the 10 respondents per item contained in the questionnaire. The PLS approach, remains to handle even the presence of a small sample (under certain conditions which we will present later) and a complex structural model. It also has great flexibility at the test models with latent variables formative and reflective, something does not allow LISREL approach under certain conditions.

Finally, the LISREL method has the advantage of testing the recursive and non-recursive models. Manipulation is not possible under PLS which deals only recursive models in which causality between the latent variables must be unique.

4. Presentation of the PLS approach

The PLS approach (Partial Least Squares), which is based on a partial least squares algorithm was developed mainly by Chatelin et al. (2002) through the work of Wold (1985) and Lohmöller (1984, 1987 and 1989). This approach has the advantage of checking several links between several explanatory variables and explain at different levels. It also has the advantage of not requiring a large number of observations and does not require a normal distribution of database. The PLS approach also seems appropriate for studies where measurements are not very precise, it is quite the spirit of data analysis (Tenenhaus, 1998).

The approach of the PLS approach starts on the basis of the theoretical model specified by an iterative estimation, first on the measurement model, maximizing the explanatory power of the weighted indicators and combined with estimates of latent variables. Then, on the structural model, estimating the relationships between latent variables by multiple regressions between selected variables, and to maximize the covariance between independent variable and dependent variable (Sosik et al. 2009).

The PLS approach then allows to model the data directly on the basis of a series of multiple regressions without starting probabilistic assumptions, unlike the LISREL approach. It therefore does not require conditions multinormality as is the case with the analysis on the covariance or conditions in relation to the nature of the data. The PLS approach also allows simultaneous testing of reflective and formative latent variable that does not allow the LISREL approach.

If this approach all these advantages, its distribution remains limited because of some limitations in its approach. Indeed, the PLS approach does not take account of measurement errors which reduces the quality of the estimate measures, this results in an underestimation of structural relationships and overestimate the contribution factor (loadings). One solution is possible to exceed this limit (Mc Donald, 1996), is to hold a large number of items per latent variable, and have an extremely large number of observations.
Another limitation inherent to the PLS approach is that relating to the testing of non-recursive models. Indeed, the PLS approach allows to test the causal relationships since univocal models based on multiple regression procedures.

Finally, a limit that led to the rejection of some scientific articles in international journals (Chin, 1998), is inherent in the absence of model adjustment indices (Fit indices) as part of the PLS approach. Indeed, these indices to judge the fit of the model to empirical data. Nevertheless, there are some calculations that can ensure the significance of the coefficients, based on factor inputs and coefficients of determination.

5. Relevance of the PLS approach to research in inter organizational context: the case of research in logistics.

As we mentioned above, the PLS approach is suitable for exploratory analyzes and testing of partial models, in which the researcher does not often enjoys a large sample or robust measurement scales (Sosik et al. 2009; Lacroux, 2010), which is often the case in research that are part of such a young discipline logistics Management, which are inter organizational perspective. Indeed, despite the fact that several logistics studies follow a fashion confirmatory reasoning to confirm the theory in a specific empirical field, this research often have an exploratory empirical context.

Another element seems important to raise. The PLS method seems suitable for complex structural models, ranging according to (Lacroux, 2010) up to hundreds of variables, which is often the case in the context of structural models in logistics (Balambo, 2012; 2013).
The PLS method can also test models based on a small sample, that does not allow the LISREL approach. Indeed, the PLS approach requires empirical rule that the number of observations is greater than or equal to 10 times the number of indicators of formative variable most complex and / or 10 times the number of structural relationships from central built structural model (Chin, 1998). In this sense, we believe this flexibility in the narrowness of the sample can open the door to school interested in inter organizational context of logistics, where it is difficult to gather a large number of observations, as the main unit of analysis remains the company. Many studies interested in inter-organizational relationships in Logistics and whose unit of analysis is the dyad, the network, or the company have difficulty be large enough samples to meet the requirements of the LISREL approach, while the PLS approach seems an effective alternative that can overcome the condition of the largest number of the sample that is primarily allowed by the Boostraping technique.

Another element is related to the mobilization by the studies concerned with logistics in inter-organizational relationships often involving complex explanatory models to better approach the real, latent variables and constructs that can be formative or reflexive. In this sense, the PLS approach seems a flexible method for testing models simultaneously with formative and reflective variables (Lacroux 2010). Indeed, PLS is clearly suited to logistics issues for which data are collected by the questionnaire, as noted by (Sosik et al., 2009) quoted (Lacroux, 2010): "The PLS method works best in practice because Data from the field used in the modeling are never perfect, and are often highly correlated. By selecting the best linear combination to predict the dependent variables, it provides more meaningful structural coefficients that methods based on maximum likelihood (Lisrel). Lisrel type methods give their best when the data is obtained using an experimental design: gold, this type of design is rarely possible in practice, especially when data are obtained by questionnaire ".

Finally, the PLS method avoids the unacceptable solutions and uncertainty factors and provides an exact definition of the component scores.

Conclusion

The mobilization of second-generation methods, known structural equation seems inevitable in the counterfactual searches have opted for a quantitative treatment of the data collected. In this sense, PLS is an emerging method in the specific context of inter-organizational logistics relationships (two theses identified in France (Balambo, 2012;. Saikouk, 2013) This method opens up many research perspectives, combining convenience of operating the Data often difficult harvestable and a specification to correct certain variables often specified as reflexive (logistics performance, supply chain performance for example) then they are formative essence.

This opens the way for logistics researchers often mobilizing multidimensional variables such opportunism, trust, commitment, rooting ... to review the specification of variables as formative.

PLS also opens the possibility for new logistics research areas (risk management, corporate social responsibility, sustainable supply chains, ...) a better understanding and analysis of quantitative models using software such as smart Pls, and Lisrel Amos.

Bibliography

- Balambo M.A. (2012), « L'impact de la culture nationale sur la nature de l'intégration des supply chains : une étude à travers l'effet médiateur de la nature de la confiance. Une application aux équipementiers automobiles marocains », Thèse de doctorat en sciences de gestion, CRETLOG, Aix-Marseille Université.

- Balambo M.A., (2013), « Culture nationale et nature de l'intégration des supply chains amont: le cas des équipementiers automobiles marocains », *Revue Logistique & Management*, Volume 21, Numéro 4, pp. 71-82(12). Numéro spécial : Globalisation et Supply Chain Management.

- Bentler, P.M. (1980), « Multivariate analysis with latent variables: Causal modeling », *Annual Review of Psychology*, 31, 419-456.

- Chin, W. W. (1993-2003). PLS Graph – Version 3.0. Soft Modeling Inc.

- Chin W.W. (1998), « The partial least squares approach to structural equation modeling », *In* G. A. Marcoulides (Ed.), *Modern methods for business research*, (pp. 295-336), Mahwah, NJ: Lawrence Erlbaum.
- El Akremi A. (2005), « Analyse des effets linéaires, non linéaires et d'interaction par les méthodes d'équations structurelles sous Lisrel », *in* Roussel P., Wacheux F., *Management des Ressources Humaines : Méthodes de recherche en sciences humaines et sociales*, Paris, De Boeck.

- 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.

- Joreskog, K. G. (1966), « Testing a simple structure hypothesis in factor analysis », *Psychometrika*, 31, 165-178.

- Lacroux A. (2010), « L'analyse des modèles de relations structurelles par la méthode PLS : une approche émergente dans la recherche quantitative en GRH », *XXème congrès de l'AGRH,* Toulouse

- Livolsi, L., Meschi, P.-X. (2003). Méthodologie quantitative de la recherche en gestion des ressources humaines, in Allouche, J. (éditeur), *Encyclopédie des Ressources Humaines*, *Vuibert*, Paris, pp. 897-908.

- MacKenzie, S.B., Podsakoff, P.M., and 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.

- Mc Donald, R. P. (1996), « Path analysis with composite variables », *Multivariate Behavioral Research*, 31,239–270.

- Ringle, C. M., Wende, S., & Will, A. (2005), *SmartPLS* 2.0 (M3) beta, Hamburg: http://www.smartpls.de.

- Roussel, P., Durrieu, F., Campoy, É., El Akremi, A., (2002), « Méthodes d'Équations Structurelles : Recherche et Applications en Gestion », *Économica*, Paris

- Sosik, J., Kahai, S., & Piovoso, M. (2009), « Silver Bullet or Voodoo Statistics? A Primer for Using the Partial Least Squares Data Analytic Technique in Group and Organization Research», *Group & Organization Management*, 34(1), 5-36.

- Tenenhaus, M. (1998), *la régression PLS, Théorie et Pratique*, Editions Technip.

- Valette-Florence P. (1988), *L'implication, variable médiatrice entre les styles de vie, valeurs et mode de consommation*, Thèse de science de gestion, Université de Grenoble.