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Spanish Customer Satisfaction Indices by Cumulative Panel Data

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Abstract

In this paper, we present a new theoretical representation of the Consumer Satisfaction Index (CSI) based on Structural Equation Modeling (SEM). We use panel data collected by an automotive magazine to apply our approach and assess the applicability in the field of marketing by formulating a competitive strategy in the Spanish automobile industry. The basic structure of the CSI is based upon well established theories and approaches to customer satisfaction (see Fornell 1992; Fornell et al., 1996). The structure based upon these theories consists of a number of latent factors, each of which is operationalised by multiple measures. The purpose of this paper is to propose a new way of representing the structure of Spanish Consumer Satisfaction (CS) in the automobile industry to study and compare the implications of its representations. We will discuss that CSI is a global evaluation constructed on the basis of its particular component evaluations. Apart from building a new way of representing the structure of CS, this work tries to correct for the bias produced by the particular method of calculus employed by the magazine.

Key words: SEM; Factor Analysis; Cumulative Panel Data.

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1 Introduction

Nowadays, the measurements of satisfaction indices are used as quantitative outcomes in very different fields of the economy but they are mainly applied in marketing. However, the way those indices have been calculated is not always the proper one.

We have a three period panel data obtained from *Autopista* magazine readers' answers. The panel is composed of several satisfaction indices of 112 models of cars calculated in a specific way. The indices are calculated by as average of all answers of the previous periods and the current one. This way of calculation leads us to a systematic bias.

We consider that this way of calculation is not proper in order to analyze any change in consumer satisfaction throughout the time. However, as the measurement instruments and the data sources are limited, we propose the development and application of methodologies that fit with all kind of data without interpreting the results wrongly. If we did not take into account the existence of this bias, we would be overestimating or underestimating the correlation between the observed variables and therefore, the obtained fit would not be the correct one. Thus, one of the objectives of this paper is the correction of this bias which is contained in the data.

Finkel (1995) states that the structure of the panel data allows to estimate models with measurement error, assuming less number of constraints than in the context of cross section. The usual panel data models (regression models) assume that variables have been measured without error. Nevertheless, in most of the important fields as in social sciences, the available instruments obtain measures in an imperfect way. These instruments could be the behavioral surveys or the published aggregated statistics. As long as the observed variables contain measurement error, the estimations of the structural coefficients in the regression models would not be correct. The measurement errors could indicate changes in the variables along time when in fact no change has taken place. Therefore, this is a serious issue in the panel data models.

The bias in Ordinary Least Squares (OLS) estimations and estimations with measurement errors, appears due to the correlation between the independent variable and the error term. A solution might be the use of an exogenous variable that is related with the *"true-score"* (latent variable) which is not related with the random error term of the model. Using cross section data, there are two models to solve the problem of the error term. The first one is well known as the instrumental variables method and the second as the two step least squares estimation. With panel data, however, there are alternative strategies to manage with problem of the error term. Those alternative strategies in most cases would be preferable to the instrumental variables method or the two step least squares (Finkel (1995)).

One way of dealing with the measurement error, in the structural equation models is the multiple indicators approach, in which several measures of the same latent variable are used to estimate not only the structural effects but also the measurement parameters. Moreover, in panel designs, the repeated measurements of the indicators along time increase the strong point of this method and the additional data offer more information for estimating relevant structural and measurement coefficients.

We consider some models in which the vector of observed variables y is structured as a linear function of more basic variables that might be latent or not observed. A typical example may be the factor analysis:

$$y = \Lambda\xi + \epsilon$$

where Λ is a parameter matrix ($p \times p$) and ξ and ϵ are the vectors of the common and specific factor ($p \times 1$) respectively that are supposed to be uncorrelated.

Let vector θ contain the unknown parameters of any covariance structure model. A structural model must be able to reproduce the covariance matrix Σ of dimension $(p \times p)$, using the parameters of θ. Hence, the variance and covariance matrix Σ is expressed in function of θ, that is, $\Sigma = \Sigma(\theta)$. The problem of estimating the parameters is to find the values of θ so that the estimated variance and covariance matrix, $\hat{\Sigma} = \Sigma(\hat{\theta})$, is close to S. If the model is correctly specified, the discrepancy $(S - \hat{\Sigma})$ should be small.

We assume that the independent observed variables have a normal multivariate distribution and estimate the model applying the maximum likelihood method with full information. The goal is to minimize the discrepancy function Browne (1974) in the context of a covariance structure analysis, defined as

$$g = (S^* - \Sigma^*)' W^{-1} (S^* - \Sigma^*) \ , \tag{1}$$

where S^* and Σ^* are the reduced vectors composed of $p(p+1)/2$ elements of S and Σ, respectively and W is the positive definite weighted matrix that measures the discrepancy between S^* and Σ^*. Browne called these estimators of expression (1) the estimators of Generalized Least Squares.

If the modelling of $\Sigma(\theta)$ is appropriate and the assumption of normality of the observed data is fulfilled, then the statistic[1] $T = ng$, being n the number of individuals, is distributed as a χ^2 with a number of degree of freedom equal to the difference between the number of non duplicated elements of S and the number of free parameters in θ.

[1]This value can be used as an indicator of the goodness of fit.

In an ordinary factor model, there are a number of factors that are arbitrarily correlated. Those factors, which are directly related with the indicators of the measured variables, are often called first order factors. Besides, there are other models whose factors are decomposed in another factors (Bentler (1976) and Bentler & Weeks (1980)). In this way we get a higher degree of abstraction captured through the influence of a second order factor. In this case, the correlation between the first order factors will no longer be a parameter of the model, due to the fact that the first order factors are now dependent variables of the second order factor and they cannot have variance or covariances as parameters. Thus, any covariation between the first order factors will be explained by a second order factor.

The general equations for a Second Order Factor Analysis Model are:

$$y = \Lambda_y \eta + \epsilon$$

$$\eta = \Gamma_y \xi + \zeta$$

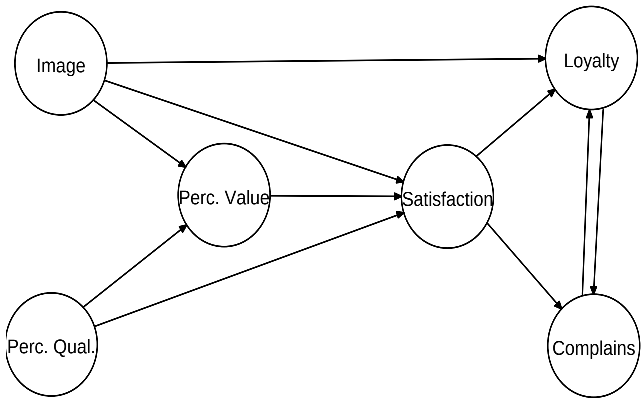
where η is $(p \times 1)$ vector of first order factors, ξ is a $(q \times 1)$ vector of second order factors, Λ_y and Γ_y are matrices of factor loadings, $(p \times p)$ and $(q \times q)$ respectively, for factors of first and second order, y is a vector of measures and finally, ζ and ϵ are the error terms.

In a measurement model a *concept* is related to one or more latent variables, and these are related to observed variables (Bollen (1989)). There are abstract *concepts* (intelligence, expectations etc.) or specific (age, sex, etc.) concepts. The *Consumer Satisfaction* (CS) is the concept we want to analyze. This *concept* is an unmeasured variable represented by two kinds of latent variables, on one hand latent variables that indicate the Partial Satisfaction of the Consumer (PSC) and on the other hand those that indicate the Global Satisfaction (GS).

In this paper, we propose some causal models based on data from the automobile industry, using the structural equation modelling methodology. All of them are simple measurement models defined as a Second Order Factor Analysis model which were established in a previous work for the first of the three periods (Fernández, López & Mariel (2003)).

A new structure designed in this paper is based on the direct measure of the consumer satisfaction and is inspired by the structure of the indices published in the previous articles which are based on a cause and effect system (Fornell (1992)). These models related the antecedents (expectations, image, perceived quality and value) to the consequences of the satisfaction (loyalty of the consumer and the claims). As we can see in Figure 1, the antecedents are: the perceived quality of the product, measured through the evaluation of the recent experience of consumption, the image that consumers get from the product, brand or company and the perceived value, related to the price of the product. On the other hand, the consequences are the loyalty, that is, the probability of repeated purchase, the mouth to mouth effect, and the number of claims.

Figure 1: **Cause/effect diagram of the satisfaction**



When defining the CS we state several questions. Is the CS a global evaluation, an evaluation of its components, or a global evaluation based on the evaluation of its components? The existing literature suggests that CS is a global evaluation made after the acquisition of a good (Fornell (1992, p. 11)). In this article we propose a new way of representing the structure of CS to analyze and compare the implications of its representations. We will focus on CS as a global evaluation based on the evaluation of its components. In Fernández et al. (2003), we propose a new structure for consumer satisfaction in the Spanish automobile industry market which is generalized to the case of panel data.

This paper is organized in the following way: the next section describes the data, section 3 specifies the model suitable for panel data, section 4 sets out the results and, finally the last section summarizes the conclusions.

2 The data

The data come from the readers' answers to a survey of the Spanish magazine *Autopista*. It was carried out by an answer card that readers sent by post. The information was collected in thirteen periods of time, from April of 1995 to June of 2001. Taking a random sample from the answers, the magazine tests the truthfulness of the data about owners, brand, model and registration number. Finally, we obtained a list of 112 models of cars common to all the periods of the panel data that consists of the observations or individuals of the sample. As the total number of received answers was $427\,340$ we can say that these 112 models of cars nearly represent the population of existing car models.

The consumers expressed their degree of satisfaction about 25 attributes such as design, habitability, security, steering, fuel consuption, confort, etc. by a value x_{jh}= -2, -1, 0, +1, +2 that reflected their level of satisfaction (very dissatisfied, dissatisfied, indifferent, satisfied and very satisfied) where j refers to each one of the attributes and h to each one of the 112 models of cars. The magazine, applied the formula $y_{jh} = 2,5(x_{jh} + 2)$ to transform these indices that range between 0 and 10. To obtain a partial consumer satisfaction index for each of the attributes, the magazine computed the average mark taking into account the total number of answers in every period, that is to say, it aggregates the results of the individuals forming by this way a "cumulative" panel data.

The total number of answers along all 13 periods of time[2] is $427\,340$, corresponding $32\,550$ to period number eleven, $31\,485$ to period number twelve and $30\,669$ to period number thirteen. Thus, our cumulative panel data will consist of these last three periods of time. Nevertheless, and due to the cumulative features of the method of calculation used by the magazine, in period number eleven, the indices are calculated using the answers of $365\,186$ individuals, in period number twelve, with the answers of $396\,671$ individuals and in period number thirteen with the answers of $427\,340$ individuals. Therefore, to obtain the indices, the magazine has employed three types of aggregations: in first place, the aggregation is done by those who have been polled of by a generalization of situations referred to a specific issue (Magnusson & Bergman (1990*a*)), in second place, the magazine aggregates the answers of the individuals, improving the reliability of the data (Magnusson & Bergman (1990*a*)), and in third place, in each period, the magazine aggregates data obtained in previous periods to the data from the current period.

3 Model specification

As stated in the previous section, we have cumulative measures about the satisfaction throughout several periods of time. Moreover, the measures of the cumulative satisfaction in the second period depend on the measures of the first period and the measures of satisfaction in the third period depend on the measures of the first and second period. This specific method of calculation of the measures employed by the magazine produces a systematic bias on their indicators.

[2]The thirteen periods are the following: 04/1995-06/1995, 09/1995-12/1995, 06/1996-08/1998, 11/1996-02/1997, 04/1997-07/1997, 10/1997-12/1997, 03/1998-05/1998, 09/1998-12/1998, 03/1999-06/1999, 10/1999-12/1999, 03/2000-06/2000, 10/2000-12/2000, 04/2001-06/2001

In order to take into account this bias we establish a causal relationship between the same measures that belong to different periods of time. If we take into account only the first two periods of time, we can establish a causal relationship that makes the measure of the second period depend on the measure of the first period. Apart from this causal relationship, we build a second order factor analysis model for the measures of each period.

The theoretical models built in every period are identical and they are based on a model which fits to the data of the first period (period 11) was satisfactory. In the previous paper Fernández et al. (2003) the estimated models were based on a single period of the same data (period 11) and after the Exploratory Factor Analysis with five factors, we determined the existence of three global satisfaction factors: the first one measured by the variables *interior-finishing*, *driving panel*, *security*, *brakes*, *reliability* and *post-sale service*; the second one measured by the variables *steering*, *gear change*, *acceleration/recovering* and *top speed*; and finally, the last factor measured by the variables *comfort*, *habitability* and *boot*. For each factor we will propose a model that will be denoted as model 1, 2 and 3.

The first two models have a second order factor structure and the third has only a first order factor structure. In the present paper, the models will be based on a matrix of variances and covariances that is made up of variables of a panel data.

The establishment of a covariance between first order factors is equivalent to propose a Second Order Factor Analysis model (SOFA) whose second order factor takes into account all the covariances between the first order factors. We specify a SOFA model imposing a covariation between the first order factors.

The proposed model is

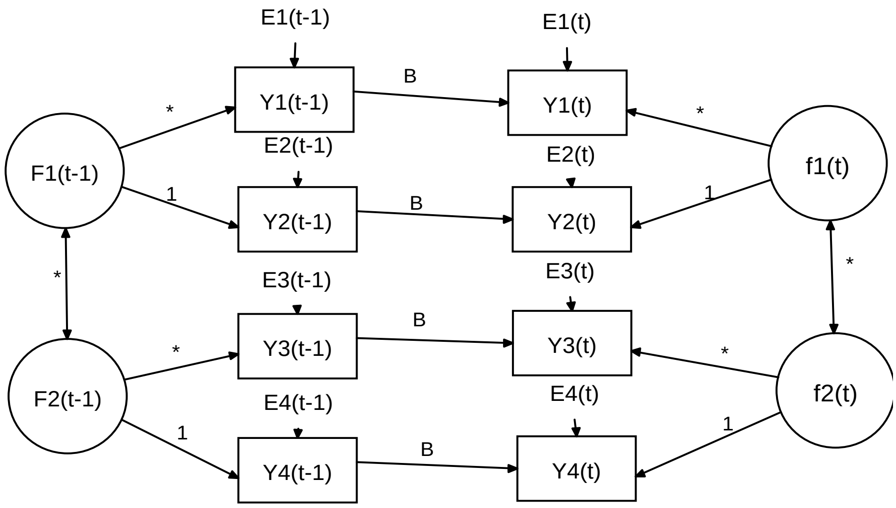
$$y_t = \beta y_{t-1} + \Lambda \eta_t + \epsilon_t \ , \tag{2}$$

where β and Λ are $(n \times n)$ matrices that contain the unknown parameters, y_t and y_{t-1} are $(n \times 1)$ vectors of observed variables, η_t is $(n \times 1)$ vector of latent variables and ϵ_t is ($n \times 1$) vector of the error term.

We assume that β is a constant for all the measures or variables. Besides, we also assume that the factor loadings matrix Λ is constant along the periods. If we assumed that the factor loadings matrices are not equal that would imply a qualitative change of the meaning as well as of the measurement of the latent variable and in our case it would be difficult to justify theoretically.

A simple example for the two periods and two underlying factors is represented in the *"path diagram"* of the Figure 2. We denote the accumulated satisfaction till the former period by F_{t-1}, the own satisfaction of period t by f_t and E are the random error terms of each period. Finally, β represents the weight of the accumulated satisfaction from the previous periods contained in the current observed satisfaction. We represent in Figure 2 a model with only two periods of time composed each one by four measures and two factors in order to make our model understandable in spite of the fact of estimating a similar model of three periods with our data.

Figure 2: **"Path diagram" representation**



As can be seen in Figure 2, we assign the unity to the first parameter λ of each latent variable η in order to fix the scale of the measurements as recommended by Joreskog & Sorbom (1978). The unknown parameters λ and the covariances between factors are represented by asterisks.

The unidirectional arrows indicate a causal relationship between two variables. The variable pointed by the arrow is the dependent and the other is the independent variable. Moreover, the bidirectional arrows represent two variables which covariate.

In short, the Figure 2 could be represented in the following way:

$$y_{p,t} = \beta y_{p,t-1} + \lambda f_{q,t} + \epsilon_{p,t} \quad (3)$$

being $y_{p,t-1} = \lambda F_{q,t-1} + \epsilon_{p,t-1}$. Where $p = 1, 2, 3, 4$ are the indicators per latent variable or factor and $q = 1, 2$ are the factors.

This last expression summarizes what in equation (2) was proposed as our model and what we can observe in the *"path diagram"* of Figure 2 for two periods of time. On one hand we have the causal relationship established for the same measures of the different periods and on the other hand, basing on the structural equation models, we relate the current measures, with the present satisfaction and a random measurement error.

Our models have a first order autorregressive structure to which a latent variable is added in order to model the behavior of the current period. The methodology of the structural equation models makes possible to define this kind of model.

4 Results

Table 1 (Appendix) presents the comparison between the specification of a SOFA model without causal relationship between the measurements and a SOFA model with causal relationship for the three models described in Fernández et al. (2003). As our panel data consists of three periods of time, we estimate the three models for two and three periods respectively. Thus, we can test the fit of our model when the data matrix is augmented.

In first place, we can analyze the goodness of fit of our measurement models through the χ^2 statistics. The usual assumption is that the variables have an elliptical or normal distribution (Bentler (1998)). If this assumption is false the test statistic for the validation of the proposed model might not have the expected χ^2 distribution. Hence, we should use another statistic test with better behavior against a wrongly specified distribution. Satorra & Bentler (1988) and Satorra & Bentler (1994) proposed some corrections for the standard goodness of fit test in order to obtain a distribution more similar to a χ^2. Therefore, we employ not only the standard χ^2 statistic but also the χ^2 statistic of Satorra and Bentler (SB).

Apart from the proposed indicators of global fit test, there are other indicators such as the normed (NFI) and nonnormed (NNFI) goodness of fit index. The second index (NNFI) is a correction of the first index (NFI) as it could be affected by the sample size. Other indices of the goodness of fit, such as the comparative goodness of fit index (CFI) and the robust comparative goodness of fit index (RCFI) try to avoid the underestimation of fit that usually appears in the case of NFI in small samples and at the same time their sample variabilities are less than in the case of NNFI.

Generally, the value of these indices range between zero and one, but sometimes their values could be negative or greater than one (Bentler (1998, p.114)). When the value of the indices is close to one the model fits the data correctly.

On the one hand, if we compare the specified model without causal relationship between the same measures of different periods of time and the model specified with causal relationship we observe that the χ^2 statistic decreases significantly. This is a first reason which indicates that the SOFA model with causal relationship fits better our data. On the other hand, the indices for the goodness of fit are next to one for the case of the SOFA model with causal relationship.

Focusing on the SOFA model with causal relationship, and comparing the *p values*, not only the standard χ^2 statistics but also the SB χ^2 statistic, we observe that the second value is always bigger than the first. In these cases, the proposed SB χ^2 statistic is more reliable than the standard one.

Finally, each SOFA model is estimated for two and three periods of time. If we compare the results of the statistics and fit indices we can determine that there is no significant change that indicates that our model when the data matrix is augmented is no longer coherent with the established specification for the variables.

Analyzing the results of the Table 1 we can state that the specification of our model is based on a SOFA model for each period of time and at the same time there are some causal relationship between the same measures of two consecutive periods. This causal relationship is used as a way for treating the cumulative information.

Table (2) – Table (7) (Appendix), present the decomposition of the direct and indirect effects that the factors and the rest of the measures have over the measures when the models with causal relationship have already been estimated.

We find in the horizontal direction the variables or measures of each model and vertically the factors that relate directly or indirectly with those variables together with the variables of each period that relate causally with those of the next period. Moreover, an horizontal line divides the variables of one period from the other and a vertical line divides the factors from the variables.

Thus, Table 2 – Table 7, which summarize the six models, are divided into four or six quadrants depending on whether the number of periods is two or three respectively. For example, in the upper left quadrant of Table (2), we find the direct variable-factor effects. These weights or coefficients indicate the λ values of equation (3). In the second lower left quadrant, we find the direct and indirect variable-factor effects. The relationship between a measure and a factor of the same period is called direct effect and the relationship between a measure and a factor of different periods of time indirect effect. From equation (3) we obtain that $y_{p,t} = \beta(\lambda F_{q,t-1} + \epsilon_{p,t-1}) + \lambda f_{q,t} + \epsilon_{p,t}$ and we call indirect effect the relationship between $y_{p,t}$ and $F_{q,t-1}$. Finally, in the lower right quadrant we find the causal effects between the measures of different periods which are called β.

As the values are standardized, the closer to one the value is, the bigger the effect of the factor over the variable will be.

In all six models, the direct and the indirect effect of the variables with the factors of the first period is very strong and close to one. Nevertheless every effect of the variables with the factors of the different periods is very low and close to zero. This means that we have different kinds of factors in our model. As could be seen in the Figure 2 there are two type of factors. The first one corresponds to the accumulated factor (F) and the remaining factors represent the own satisfaction (f) for each period.

The cumulative answers for first period is $365\,186$. The cumulative satisfaction of these individuals is represented by the factors of the first period. However, the factors of the second and third periods take into account only the satisfaction of $31\,485$ and $30\,669$ individuals respectively.

On the other hand, the causal relationship between the measures of different periods is very high. It indicates that the value of β or the weight of the accumulated satisfaction up to the previous period is very high.

Analyzing these results we can observe a clear difference between the factors of the first and remaining periods. The factors of the first period take into account the satisfaction accumulated up to their period while the factors of the following periods take into account the consumer satisfaction in the current period.

5 Conclusion

In the present paper, we obtain several conclusions from the methodological and conceptual point of view. Regarding the methodology, firstly we validate once more the structure of the model analyzed in Fernández et al. (2003) and determine that CS is a global evaluation based on the evaluations of its components and structured as a SOFA model. Secondly the lack of causal relationship between the measures of different periods invalidate the estimation of variances and covariances and therefore biases the estimations of the measurement effects.

The magazine *Autopista* has published several satisfaction indices one for each period of time in which the survey was carried out. However, using this method of calculation only biased accumulated indices can be obtained. That is why the published indices are not representative values for each period.

The methodology of the structural equation models permits to take into account this systematic bias and obtain some representative and innovative factors for the satisfaction indices of each period. Nevertheless, the data constraints of our panel data (only three periods) makes this study a small example of what could be obtained if we had a panel with all the thirteen periods published by the magazine.

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6 Appendix

Table 1: **Indicators for the goodness of fit of three models**

	χ^2 (df)	*p value*	χ^2 (SB) (df)	*p value*	NFI	NNFI	CFI	RCFI
Model 1								
2 periods panel								
FOFA (without causal relationship)	1751,073 (51)	$< 0,001$	1081,417 (51)	$< 0,001$	0,342	0,153	0,345	0,474
SOFA (with causal relationship)	114,127 (50)	$< 0,001$	71,817 (50)	$0,023$	$0,957$	$0,967$	$0,975$	$0,989$
3 periods panel								
FOFA (without causal relationship)	3054,953 (132)	$< 0,001$	413,668 (132)	$< 0,001$	0,306	0,203	0,312	0,904
SOFA (with causal relationship)	262,742 (130)	$< 0,001$	180,344 (130)	$0,0023$	$0,940$	$0,963$	$0,969$	$0,983$
Model 2								
2 periods panel								
FOFA (without causal relationship)	1262,194 (21)	$< 0,001$	910,704 (21)	$< 0,001$	0,360	0,148	0,361	0,260
SOFA (with causal relationship)	47,606 (20)	$< 0,001$	33,867 (20)	$0,027$	$0,976$	$0,980$	$0,986$	$0,988$
3 periods panel								
FOFA (without causal relationship)	1921,484 (55)	$< 0,001$	1519,574 (55)	$< 0,001$	0,330	0,201	0,334	0,345
SOFA (with causal relationship)	94,904 (53)	$< 0,001$	72,029 (53)	$0,042$	$0,967$	$0,981$	$0,985$	$0,991$
Model 3								
2 periods panel								
FOFA (without causal relationship)	1193,843 (10)	$< 0,001$	832,614 (10)	$< 0,001$	0,151	$-0,420$	0,148	0,118
SOFA (with causal relationship)	19,057 (9)	$0,039$	14,762 (9)	$0,140$	$0,986$	$0,990$	$0,993$	$0,995$
3 periods panel								
FOFA (without causal relationship)	2157,788 (31)	$< 0,001$	1735,283 (31)	$< 0,001$	0,120	$-0,023$	0,119	0,086
SOFA (with causal relationship)	46,763 (29)	$0,019$	40,776 (29)	$0,072$	$0,981$	$0,991$	$0,993$	$0,994$

Table 2: **Direct and indirect effects decompositions with standardized values. Model 1 (two periods)**

IND.	F1	F2	F3	F4	F5	F6	Y1	Y2	Y3	Y4	Y5	Y6
Y1	0,867											
Y2	0,744											
Y3		0,934										
Y4		0,779										
Y5			0,920									
Y6			0,701									
Y7	0,834			0,248			0,961					
Y8	0,710			0,211				0,954				
Y9		0,911			0,199				0,975			
Y10		0,757			0,165					0,971		
Y11			0,847			0,297					0,921	
Y12			0,644			0,225						0,919

Y1= $inner-finishing$ (1^{st} period), Y2=$driving\ panel$(1^{st} period), Y3=$security$(1^{st} period), Y4=$brakes$(1^{st} period), Y5=$reliability$(1^{st} period) and Y6=$post\ sale\ service$(1^{st} period)
Y7= $inner - finishing$ (2^{nd} period), Y8=$driving\ panel$(2^{nd} period), Y9=$security$(2^{nd} period), Y10=$brakes$(2^{nd} period), Y11=$reliability$(2^{nd} period) and Y12=$post\ sale\ service$(2^{nd} period)

Table 3: **Direct and indirect effects decompositions with standardized values. Model 1 (three periods)**

IND.	F1	F2	F3	F4	F5	F6	F7	F8	F9	Y1	Y2	Y3	Y4	Y5	Y6
Y1	0,844														
Y2	0,783														
Y3		0,929													
Y4		0,812													
Y5			0,994												
Y6			0,644												
Y7	0,823			0,177						0,975					
Y8	0,760			0,163							0,970				
Y9		0,917			0,145							0,987			
Y10		0,793			0,126								0,976		
Y11			0,948			0,184								0,953	
Y12			0,607			0,118									0,943
Y13	0,772			0,166			0,229			0,915					
Y14	0,713			0,153			0,211				0,911				
Y15		0,872			0,138			0,233				0,939			
Y16		0,741			0,117			0,198					0,912		
Y17			0,880			0,171			0,251					0,885	
Y18			0,579			0,113			0,165						0,898

IND.	Y7	Y8	Y9	Y10	Y11	Y12
Y13	0,939					
Y14		0,939				
Y15			0,951			
Y16				0,934		
Y17					0,929	
Y18						0,953

Y1= $inner - finishing$ (1^{st} period), Y2=$driving \quad panel$(1^{st} period), Y3=$security$(1^{st} period), Y4=$brakes$(1^{st} period), Y5=$reliability$(1^{st} period) and Y6=$post\ sale\ service$(1^{st} period)
Y7= $inner - finishing$ (2^{nd} period), Y8=$driving \quad panel$(2^{nd} period), Y9=$security$(2^{nd} period), Y10=$brakes$(2^{nd} period), Y11=$reliability$(2^{nd} period) and Y12=$post\ sale\ service$(2^{nd} period)
Y13= $inner - finishing$ (3^{rd} period), Y14=$driving \quad panel$(3^{rd} period), Y15=$security$(3^{rd} period), Y16=$brakes$(3^{rd} period), Y17=$reliability$(3^{rd} period) and Y18=$post\ sale\ service$(3^{rd} period)

Table 4: **Direct and indirect effects decompositions with standardized values. Model 2 (two periods)**

IND.	F1	F2	F3	F4	Y1	Y2	Y3	Y4
Y1	0,808							
Y2	0,853							
Y3		0,940						
Y4		0,957						
Y5	0,778		0,202		0,963			
Y6	0,819		0,213			0,960		
Y7		0,913		0,212			0,972	
Y8		0,929		0,216				0,970

Y1= $steering$ (1^{st} period), Y2=$gear \quad change$(1^{st} period), Y3=$acceleration/recovering$(1^{st} period), Y4=$speed$(1^{st} period)
Y5= $steering$ (2^{nd} period), Y6=$gear \quad change$(2^{nd} period), Y7=$acceleration/recovering$(2^{nd} period), Y8=$speed$(2^{nd} period)

Table 5: **Direct and indirect effects decompositions with standardized values. Model 2 (three periods)**

IND.	F1	F2	F3	F4	F5	F6	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8
Y1	0,772													
Y2	0,911													
Y3		0,982												
Y4		0,901												
Y5	0,749		0,174				0,971							
Y6	0,864		0,200					0,949						
Y7		0,960		0,182					0,978					
Y8		0,880		0,167						0,977				
Y9	0,700		0,162		0,149		0,907				0,935			
Y10	0,789		0,183		0,168			0,866				0,912		
Y11		0,888		0,169		0,357			0,905				0,925	
Y12		0,813		0,154		0,326				0,902				0,923

Y1= $steering$ (1^{st} period), Y2=$gear\ \ change$(1^{st} period), Y3=$acceleration/recovering$(1^{st} period), Y4=$speed$(1^{st} period)
Y5= $steering$ (2^{nd} period), Y6=$gear\ \ change$(2^{nd} period), Y7=$acceleration/recovering$(2^{nd} period), Y8=$speed$(2^{nd} period)
Y9= $steering$ (3^{rd} period), Y10=$gear\ \ change$ (3^{rd} period), Y11=$acceleration/recovering$ (3^{rd} period), Y12=$speed$ (3^{rd} period)

Table 6: **Direct and indirect effects decompositions with standardized values. Model 3 (two periods)**

IND.	F1	F2	Y1	Y2	Y3
Y1	0,876				
Y2	0,725				
Y3	0,577				
Y4	0,867	0,132	0,989		
Y5	0,715	0,109		0,987	
Y6	0,553	0,084			0,959

Y1= $comfor$ (1^{st} period), Y2=$habitability$ (1^{st} period), Y3=$boot$ (1^{st} period),
Y4= $comfort$ (2^{nd} period), Y5=$habitability$ (2^{nd} period), Y6=$boot$ (2^{nd} period)

Table 7: **Direct and indirect effects decompositions with standardized values. Model 3 (three periods)**

IND.	F1	F2	F3	Y1	Y2	Y3	Y4	Y5	Y6
Y1	0,840								
Y2	0,666								
Y3	0,681								
Y4	0,832	0,119		0,991					
Y5	0,659	0,094			0,989				
Y6	0,665	0,095				0,976			
Y7	0,813	0,116	0,156	0,968			0,977		
Y8	0,648	0,092	0,124		0,972			0,982	
Y9	0,639	0,091	0,123			0,938			0,961

Y1= $comfor$ (1^{st} period), Y2=$habitability$ (1^{st} period), Y3=$boot$ (1^{st} period),
Y4= $comfort$ (2^{nd} period), Y5=$habitability$ (2^{nd} period), Y6=$boot$ (2^{nd} period)
Y7= $comfort$ (3^{rd} period), Y8=$habitability$ (3^{rd} period), Y9=$boot$ (3^{rd} period),