TRADE SATISFACTION ANALYSIS: AN INTEGRATED APPROACH

Federica Cugnata[1]

Department of Economics and Statistics Cognetti de Martiis, University of Turin, Italy

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Abstract *This paper presents a comparative analysis of statistical methods used to evaluate trade satisfaction surveys replicated over time. More precisely, an analysis is conducted on kitchen manufacturers' and wholesalers' opinions of five major brands of built-in appliances, measured over a period of several years.*
The main objectives of the analysis are to identify strengths and weaknesses, highlight drivers of satisfaction, to compare different brands and to monitor changes over time. To achieve these goals, the CUB model, the Rasch model and Non Linear Principal Component Analysis are used, and the potential of each method is discussed from the perspective of the integrated models.

Keywords: *CUB model, Non linear principal component analysis, Rasch analysis, Ordinal data*

1. INTRODUCTION

This article presents an empirical illustration of the use of non-classic methods to analyse trade satisfaction surveys replicated over time. Founded upon the same principles as consumer satisfaction, trade satisfaction measures the attitudes of trade customers. Trade is the link between the marketer and the user. In a competitive marketplace, where businesses have to compete for customers, satisfaction of the trade with the company is increasingly critical to the success of business strategy. Implementing and aggregating new approaches to survey data analysis may prove to be effective in increasing the information quality derived from a trade satisfaction survey.

In this study several methodologies particularly suitable for qualitative data are applied: the CUB models introduced by Piccolo (2003) for the specific purpose of interpreting and fitting ordinal responses; the Rasch model originally

[1] Federica Cugnata, email: federica.cugnata@unito.it

adopted in psychometric studies and recently applied, with some changes in interpretation, to the quality satisfaction context (De Battisti et al., 2005, 2010); and the nonlinear principal components analysis (NLPCA). The intention is not to select the best model, but to combine and integrate these models to achieve a greater number of goals and higher information quality (infoQ) (Kenett and Salini, 2011; Kenett and Shmueli, 2013).

The empirical illustration comes from a group of built-in appliance manufacturers. The surveys are organised in four waves, spanning the period 2006-2012 and regards five major brands. More precisely, the data are the opinions of kitchen manufacturers and wholesalers about 14 characteristics of a built-in appliance manufacturer.

The first aim of the analysis is to study the satisfaction around each single item to obtain a ranking of items, to identify strengths and weaknesses of each brand, to identify items that differ between brands and to monitor trends and to point out areas of improvement or deterioration. CUB model and Rasch model can be used to achieve these goals. The CUB models are also used to relate observed satisfaction to respondents' characteristics. The second aim of the analysis, of great value to decision makers, is to obtain a measure of the overall satisfaction of respondents that summarises all evaluation characteristics. This objective can be achieved with Rasch model and NLPCA. Finally, by using the obtained results, it is possible to carry out an importance-performance analysis, as proposed by Ferrari and Salini (2011), to identify the drivers of satisfaction and to decide where improvement initiatives should be launched.

The paper is organised as follows: Section 2 introduces the methods, Section 3 reports results, and Section 4 draws conclusions.

1.1 THE MODELS

1.2 THE CUB MODELS

CUB models are a class of statistical models introduced by Piccolo (2003) for the specific purpose of interpreting and fitting ordinal responses. In the CUB models, ratings are interpreted as the result of two main factors: the personal *feeling* of the subject towards the item and some intrinsic *uncertainty*.

Let R be a random variable that assumes m possible categories, $r = 1,2,3,\dots,m$. Formally, the probability distribution of the CUB model is given by:

$$P_r(R=r) = \pi \binom{m-1}{r-1} \xi^{m-r}(1-\xi)^{r-1} + (1-\pi)\frac{1}{m}, \qquad r = 1,2,\dots,m,$$

where $\pi \in (0,1]$ and $\xi \in [0,1]$. The first component is a shifted Binomial random variable; $(1-\xi)$ may be understood as a measure of the *feeling* of the respondent towards the item. The second component is a Uniform random variable; $(1-\pi)$ reflects *uncertainty* in the final judgement. More specifically, $(1-\xi)$ increases when respondents choose high ratings, and vice versa. On the other hand, $(1-\pi)$ increases when the indecision in the choice of respondents is higher. This interpretation allows representation of each model as a point in the parameter space (the unit square) by comparing the models in time, between subgroups or by changing external circumstances (Capecchi and Piccolo, 2010).

In order to improve the performance of this structure, an extension of the CUB model with covariates has been proposed (Iannario, 2007; Piccolo and D'Elia, 2008). If p and q covariates are introduced to explain *uncertainty* and *feeling*, respectively, we will denote such a structure as a CUB(p,q) model. The general formulation of a CUB(p,q) model is modelled by two components:

1. A *stochastic component*:

$$Pr(R_i = r \mid \boldsymbol{y}_i; \boldsymbol{w}_i) = \pi_i \binom{m-1}{r-1} \xi_i^{m-r}(1-\xi_i)^{r-1} + (1-\pi_i)\left(\frac{1}{m}\right),$$

$r = 1,2,\ldots,m$; for any $i = 1,2,\ldots,n$.

2. Two *systematic components*:

$$\pi_i = \frac{1}{1+e^{-\boldsymbol{y}_i\boldsymbol{\beta}}}; \qquad \xi_i = \frac{1}{1+e^{-\boldsymbol{w}_i\boldsymbol{\gamma}}}; \qquad i = 1,2,\ldots,n,$$

where $\boldsymbol{y}_i = (1, y_{i1}, y_{i2}, ..., y_{ip})'$ and $\boldsymbol{w}_i = (1, w_{i1}, w_{i2}, ..., w_{iq})'$ denote the covariates of the i-th subject, selected to explain π_i and ξ_i respectively. $\boldsymbol{\beta} = (\beta_0, \beta_1, ..., \beta_p)'$ and $\boldsymbol{\gamma} = (\gamma_0, \gamma_1, ..., \gamma_q)'$ are parameter vectors. For a positive increasing y_{ik}, $k = 1,2,...,p$ (all other things being equal), the *uncertainty* $(1-\pi)$ decreases for $\beta_k > 0$, and it increases for $\beta_k < 0$. For a positive increasing w_{ik}, $k = 1,2,...,q$ (all other things being equal), the *feeling* $(1-\xi)$ decreases for $\gamma_k > 0$, and increases for $\gamma_k < 0$.

1.3 THE RASCH MODEL

The crucial hypothesis of the Rasch model is the idea that the answers to the items depend on two parameters: a parameter for items and a parameter for the user. The Rasch model was proposed in the psychometric field to study the ability of a subject to overcome or fail a test. In this context, the first set of parameters, called the item parameter, measures the difficulty of the item, while the second set of parameters, called the person parameter, measures the ability of the respondent.

Since typically the scale adopted for responses to the various items in a questionnaire of satisfaction analysis is a polytomous scale, we consider the Rasch polytomous model.

Let X_{ij} be the random variable that describes the answer of subject i ($i = 1,2,...,n$) to item j ($j = 1,2,...,k$) and can assume $m+1$ possible ordered categories ($h = 0,1,2,...,m$). In the partial credit model (PCM), the probability that subject i gives response h to item j is

$$P(X_{ij} = h) = \frac{\exp\left[h\theta_i + (h\beta_j - \delta_h)\right]}{\sum_{h=0}^{m} \exp\left[h\theta_i + (h\beta_j - \delta_h)\right]}.$$

The probability related to each category depends on three sets of parameters: the person parameters θ_i ($i = 1,...,n$), the item parameters β_j ($j = 1,2,...,k$) and the category thresholds δ_h, that is, points where two adjacent categories have the same probability of being chosen.

In the context of satisfaction analysis, the parameters' interpretation is adapted to the nature of the problem (De Battisti et al., 2005, 2012; Nicolini and Salini, 2006). The parameters θ_i reflect the user's satisfaction: a high value of this parameter indicates a high degree of satisfaction. The parameters β_j are related to the item quality: a low value of the parameter indicates a high item quality. The main utility of the Rasch model is, precisely, that it gives a ranking of the respondents in terms of satisfaction, and a ranking of the items from the one with the best quality to the one with the least quality.

1.4 NONLINEAR PRINCIPAL COMPONENT ANALYSIS

The Nonlinear principal component analysis (NLPCA) (Gifi, 1990) is a dimensionality reduction method, a generalisation of classical PCA for ordinal variables that in the field of satisfaction analysis provides to obtain a suitable measurement of satisfaction for each respondents, and a measure of importance for the items in defining an indicator of satisfaction (Ferrari and Barbiero, 2012; Ferrari and Salini, 2011).

Formally, let X be the latent variable to be measured on n units, m be the number of the ordinal variables with k_j ordered categories ($j = 1,...,m$) observed on each unit, G_j be the $n \times k_j$ indicator matrix for the j-th variable. By applying NLPCA, the vector of the respondents' satisfaction measures is the $n \times 1$ vector $\mathbf{x}$ of object scores, that minimises

$$\sigma^2(\mathbf{x}, \mathbf{q}_j, \beta_j) = \frac{1}{m} \sum_{j=1}^{m} (\mathbf{x} - \mathbf{G}_j \mathbf{q}_j \beta_j)^T (\mathbf{x} - \mathbf{G}_j \mathbf{q}_j \beta_j)$$

where $\mathbf{q}_j$ $(j = 1, ...m)$ denotes the vector that contains optimal category quantifications for variable j and, β_j is the component loading for variable j. The following restrictions are imposed:

$$\mathbf{x}^T\mathbf{x} = n, \quad \mathbf{u}_n^T\mathbf{x} = 0, \quad \mathbf{q}_j^T\mathbf{D}_j\mathbf{q}_j = n, \quad \mathbf{u}_{k_j}^T\mathbf{D}_j\mathbf{q}_j = 0$$

where $\mathbf{u}_n$ is a vector of ones of order n, $\mathbf{u}_{k_j}$ is a vector of ones of order k_j and $\mathbf{D}_j = G_j^T G_j$.

The one-dimensional solution yields the following object scores

$$\mathbf{x} = \frac{1}{m}\sum_{j=1}^{m} \mathbf{G}_j\mathbf{q}_j\beta_j$$

where the component loadings β_j are the correlations between scores and quantified variables, and hence they can be interpreted as the weights of the manifest variable j on the satisfaction indicator.

Before using the one-dimensional solution as a satisfaction indicator, it is necessary to evaluate its validity. Validity will be verified if the NLPCA solution fits well with the data, if the signs of component loadings are coherent and if the solution is stable.

2. APPLICATION

This application considers the rating of 14 characteristics of a group of built-in appliance manufacturers. Results refer to data about trade satisfaction with five major brands of built-in appliances, measured in 4 time-waves. Table 1 reports the number of respondents per brand and wave.

Table 1: Number of respondents by wave and time

	2006	2008	2010	2012
A	50	63	67	59
B	54	53	58	48
C	31	40	55	44
D	22	30	35	36
E	24	50	38	31
Total	181	236	253	218

The questionnaire contains 14 questions grouped by four dimensions: commercial area, service area, product area and promotional area. The evaluation of each item is based on a five-point scale (from 1=completely unsatisfied to 5=completely satisfied). Table 2 reports all the items analysed, grouped by area. The questionnaire also contains two respondents' coovariates: category of respondents, that is kitchen manufacturers or wholesalers, and class of built-in appliance purchases (<=0.5, Between 0.5 & 2.5 and Over 2.5 million of euros).

Table 2: Examined items by area

	com1	Ease of contact with suppliers
Commercial area	com2	Professionalism of contact personnel
	com3	Loyalty to the distribution channel
	ser1	Delivery times and punctuality in stocking
Service area	ser2	After-sales technical assistance
	ser3	Willingness to satisfy the needs of the customer
	prod1	Prices
	prod2	Average trade margin on products sold
Product area	prod3	Reliability
	prod4	Wide range of products
	prod5	Aesthetics and design
	prod6	Innovation
Promotional area	prom1	Brand awareness/Advertising campaigns to end-users
	prom2	Availability of promotional materials

The first step of this application is the Items analysis. Figure 1 shows the estimated CUB model's parameters, obtained by applying the CUB(0,0) model to all items. Note that the respondents generally express judgement with limited *uncertainty* and medium-high *feeling*. More precisely, the item involving brand awareness, *prom1*, presents the highest *feeling* and the item involving profit margin, *prod2*, the lowest *feeling*. All the items of the product dimension show very little *uncertainty*, the respondents' choices are more resolute and they are determined mostly by a feeling attitude. The item that presents gratest *uncertainty* is *com3*.

The CUB models' interpretation allows a comparison of models in time or between subgroups. To study the evolution over time, Figure 2 represents the classical CUB map Feeling vs. Uncertainty for each dimension, obtained by applying the CUB(0,0) model to each item in 2006 and again in 2012. The main trends that emerge are an improvement in the *feeling* and a reduction of the *uncertainty* over time. Wave 2006 obtains maximum *feeling* with respect to any items. In order to analyse in detail the level of *feeling* and *uncertainty*, we consider the estimates distinguished by year and brand. Figure 3 shows the estimates of the *feeling* (1-ξ) for each item. Figure 4 shows the estimates of the *uncertainty* (1-π) for each item.

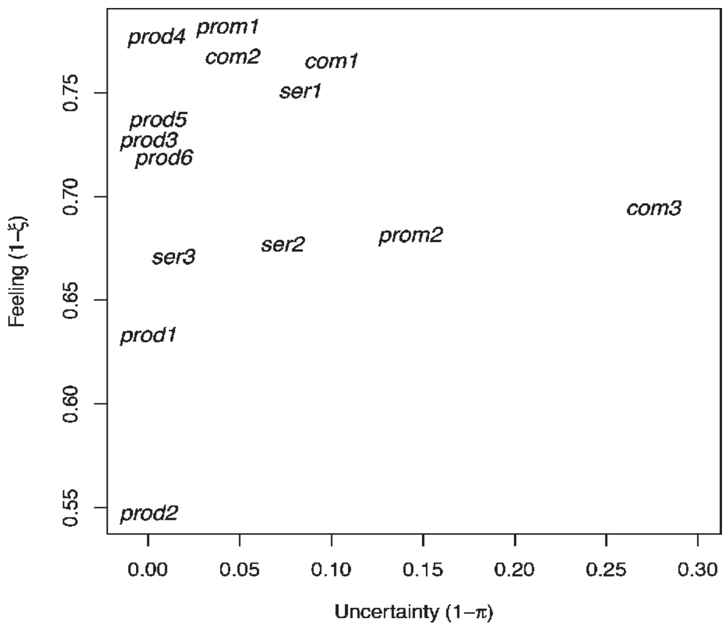


Figure 1: CUB map: Uncertainty vs Feeling

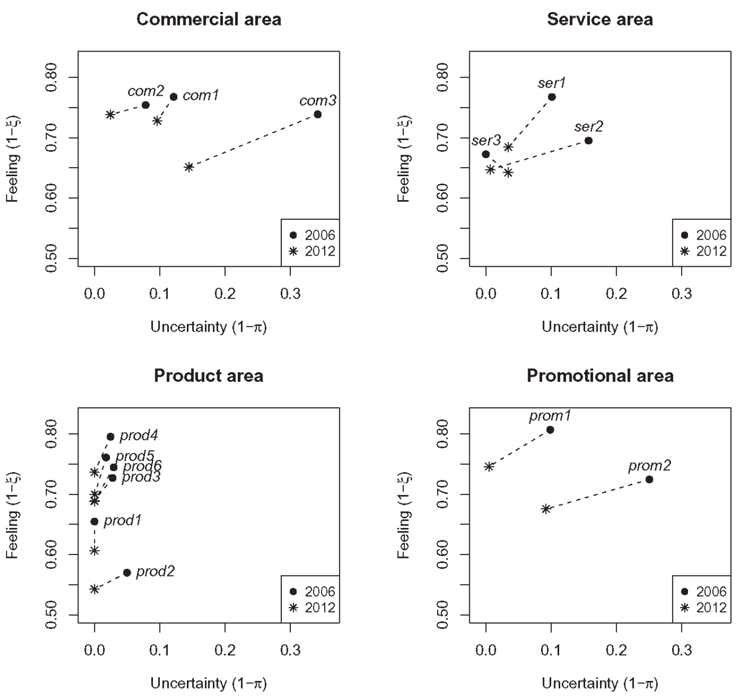


Figure 2: CUB models 2006-2012

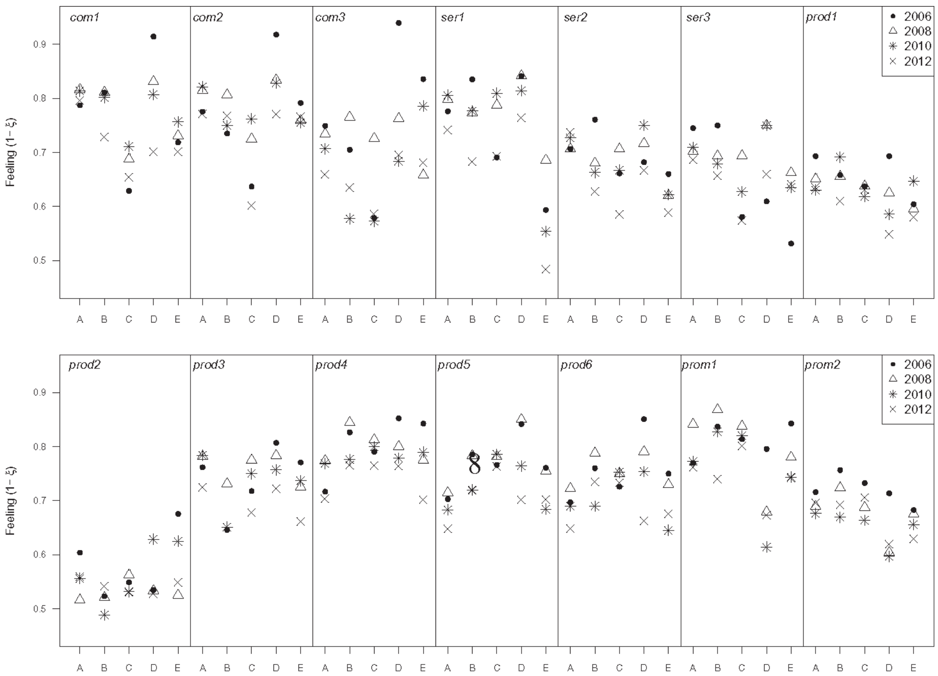


Figure 3: Estimates of the *feeling* (1-ξ) of the CUB models with respect to brands/years

First of all we can see that *feeling* is always medium-high. The lowest value is 0.5 and the highest value is 0.9. The worst item is *prod2, Average trade margin on products sold*. The greatest difference among brands is in the item involving punctual delivery, *ser1*, in which the brand E has a level of *feeling* significantly lower than the other brands. An important comment is that for most items all brands show a similar trend: an improvement in 2008 and a downturn in 2010 and 2012.

The *uncertainty* is always medium-low. The *uncertainty* is very low for the items in the product area. The other items have more uncertainty in some waves.

The CUB models could also include the covariates, category of respondents and class of purchases of respondents. Given the low level of *uncertainty*, the two covariates are tested only to explain the *feeling*. Table 3 synthesizes the results of the estimation of CUB models for all items and for each wave and each brand. The symbol (◦) means that the parameters γ_1 are not significant at 10% and + and - indicate the signs of significant parameters. For positive parameters γ_1,

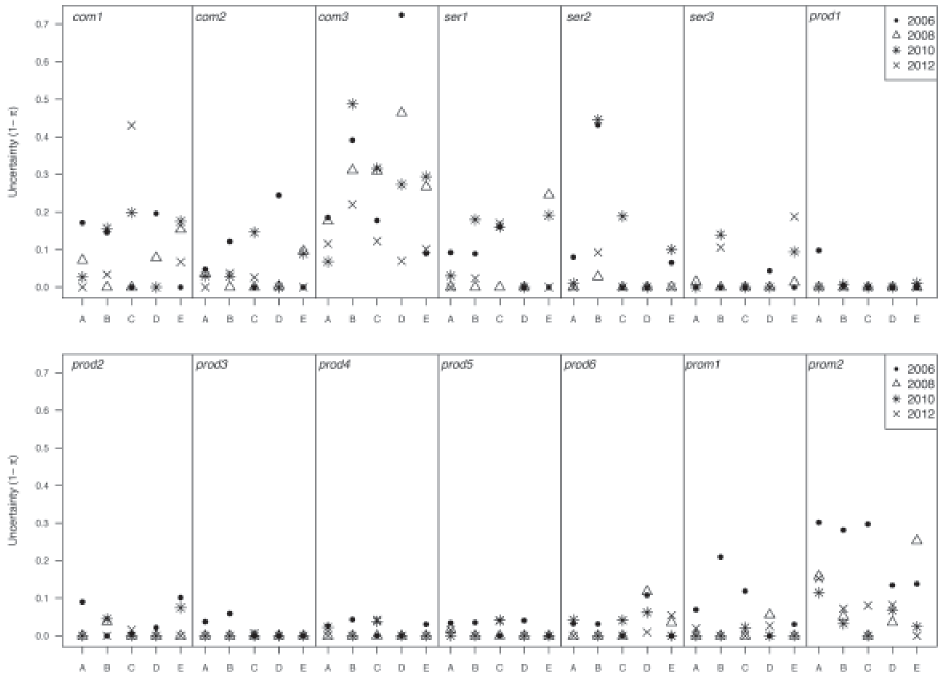


Figure 4: Estimates of the *uncertainty* (1-π) of the CUB models with respect to brands/years

the *feeling* (1-ξ) increases (decreases) when the value of the covariate decreases (increases), and vice versa for negative γ_1. Then if the class of purchases increases the *feeling* (1-ξ) decreases for the positive parmeters and increases for the negative parameters. For the dichotomous variable category of respondent, an increase of the covariate should be interpreted as moving from the kitchen manufacturers modality to the wholesalers modality. A positive parameter γ_1 means the *feeling* (1-ξ) of kitchen manufacturers is higher than that of wholesalers. A negative parameter γ_1 means the *feeling* (1-ξ) of kitchen manufacturers is lower than that of wholesalers.

As can be seen, the effect of significant covariates are monotonic among waves.

Table 3: Significance of estimated CUB model with covariates for *feeling* for each wave and for each brand

(a)

Item	category of respondents				class of purchases			
Year	2006	2008	2010	2012	2006	2008	2010	2012
com1	○	-	○	-	○	+	○	○
com2	○	○	-	-	○	○	○	○
com3	○	○	○	-	+	+	○	+
ser1	○	○	-	○	○	○	○	○
ser2	+	○	○	○	○	○	○	○
ser3	+	○	○	○	○	○	-	○
prod1	○	○	-	-	○	○	-	○
prod2	○	○	-	○	○	○	○	○
prod3	○	○	○	-	○	○	○	○
prod4	-	○	-	-	○	○	-	○
prod5	○	-	-	○	-	○	○	○
prod6	○	○	-	-	-	○	○	○
prom1	○	○	○	○	-	○	-	○
prom2	○	○	+	○	-	○	-	○

(b)

Item	category of respondents					class of purchases				
Brand	A	B	C	D	E	A	B	C	D	E
com1	○	○	-	-	-	○	○	○	○	○
com2	○	○	-	○	-	-	○	+	○	○
com3	○	○	○	-	-	○	○	○	+	○
ser1	○	○	-	○	-	○	○	○	○	○
ser2	○	+	○	○	-	○	○	○	○	○
ser3	+	○	○	○	-	○	○	○	○	○
prod1	○	○	○	-	-	○	-	○	○	○
prod2	○	○	○	-	-	○	○	○	○	-
prod3	○	○	○	○	-	○	○	○	○	○
prod4	-	○	○	-	-	○	○	○	○	○
prod5	○	○	○	-	-	○	○	○	○	○
prod6	○	○	○	-	-	○	-	○	○	○
prom1	○	○	○	○	-	○	-	○	○	-
prom2	+	+	-	○	○	-	-	-	○	-

The variable class of purchases is significant only for few items, particularly in the commercial area and in the promotional area. In the commercial area the smaller customers express more favourable opinions and vice versa in the promotional area. The variable category of respondent is more significant in 2010 and 2012. Among the brands, the variable category of respondent is significant mainly for the brand E. In general, the parameters are negative, meaning that the kitchen manufacturers are more critical than the wholesalers.

Table 4: Item location and thresholds

Item	Location	Threshold 1	Threshold 2	Threshold 3	Threshold 4
prod4	-0.056	-1.152	-1.796	0.094	2.629
prom1	0.060	-1.370	-0.975	0.193	2.394
prod3	0.173	-2.184	-0.880	0.324	3.432
prod5	0.284	-1.080	-1.318	0.560	2.975
com2	0.356	-0.631	-0.871	0.414	2.511
prod6	0.484	-0.850	-1.130	0.651	3.267
com1	0.539	-0.448	-0.419	0.679	2.345
ser1	0.573	-0.498	-0.440	0.655	2.574
ser3	0.846	-0.465	-0.929	1.250	3.527
ser2	1.000	-0.291	-0.280	1.058	3.513
prom2	1.033	-0.111	-0.182	1.204	3.222
prod1	1.075	-0.890	-0.626	1.469	4.346
com3	1.156	0.372	0.054	1.476	2.721
prod2	1.661	-0.354	0.177	2.318	4.503

An analysis of the items is carried out also by the Rasch model after checking the fit of the model. Table 4 shows item locations and thresholds. The items are ranked in decreasing order of quality rating. The item with the best quality rating (low values) is *prod4*. The item with the worst quality rating (high values) is *prod2*. In some cases the item thresholds are not monotonically increasing. This can be taken as an indicator of problems in formulations of the questions.

Figure 5 compares, for each item, the item parameters of the Rasch model with the estimated ξ of the CUB models. The quality ranking obtained through Rash models is coherent with the feeling ranking obtained through the CUB models. The items with the best quality/feeling rating are *prod4* and *prom1*, the item with the worst quality/feeling is *prod2*.

As mentioned, the Rasch model can be used to analyse the level of satisfaction of respondents. The person parameter can be interpreted as a global satisfaction index that summarises all items. Figure 6a shows the average of satisfaction for Rasch model by brands. In general the satisfaction level is decreasing over

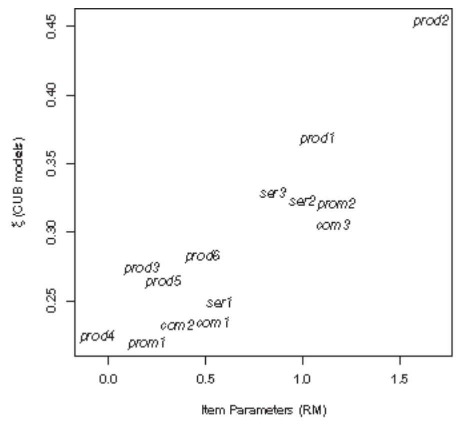
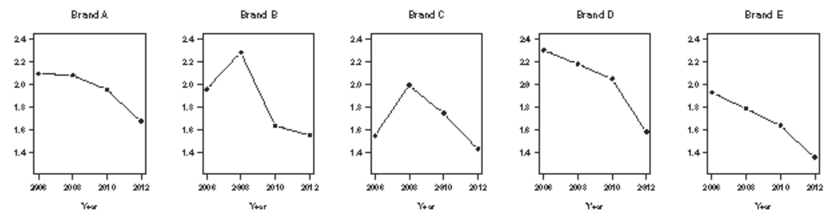
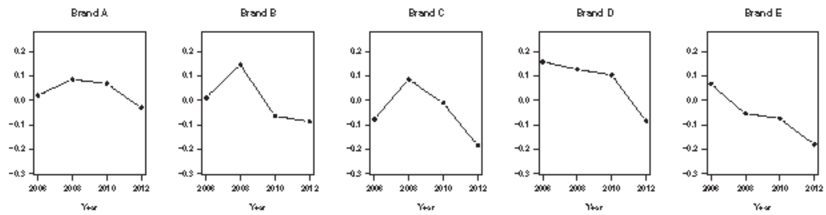


Figure 5: Item Parameters (RM) vsξ) CUB models

the years for all brands. More precisely Brand D has the highest average global satisfaction in 2006 but it is decreasing over the years. Brand C has the lowest satisfaction in 2006, has improved in 2008 and worsened again in 2010 and 2012.



(a) Rasch model



(b) Nonlinear Principal Components Analysis

Figure 7: Satisfaction by brands and by year

A similar measure of satisfaction is obtained using the object scores of NLPCA. Figure 6b shows the average of global satisfaction for NLPCA. The two methods show similar trends over time for each brand.

The NLPCA provides also a measure of importance for the items with the component loadings. Ferrari and Salini (2011) propose to combine the factor loading of NLPCA with the item parameter of the Rasch model to obtain a map importance-performance. In Figure 7 each item is represented by its component loading (x-axis) and Rasch item parameter (y-axis). Items that have high importance and high quality are the strength of the manufacturers. Items that fall in the upper right, *com3* and *prod1*, are relevant for the level of global satisfaction, but their quality is low. These items represent key areas that need to be improved with top priority.

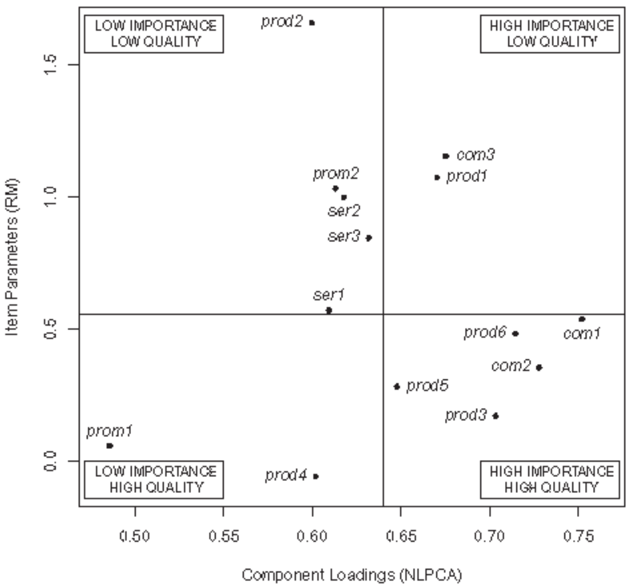


Figure 7: RM item parameters *versus* NLPCA component loading

3. CONCLUSION

This paper discussed the use of three different methods for measuring and comparing trade satisfaction expressed towards built-in appliance manufacturers in the years 2006-2012. CUB models and Rasch models permit the study of the item performance. The ranking obtained with the CUB model is consistent with the one obtained with the Rasch item parameters. The CUB models are also used to compare the *feeling* and the *uncertainty* of each item over time and for each brand, and to relate the *feeling* attitudes to respondents' characteristics. With regard to overall satisfaction, the estimates of the Rasch person-parameter and the object scores of NLPCA can be used. The two methods show a similar trend over time for each brand. Finally, NLPCA highlights those items that are more important to evaluate built-in appliance manufacturers.

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