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Dynamic profiling through repeated surveys: a customer satisfaction study

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Customer Satisfaction management has been long studied as a cross-sectional phenomenon. Today, a shift in emphasis from a static to a dynamic approach appears to be a worthwhile change, although the design and monitoring of panel data is not simple to achieve. In our paper, we propose the usage of pseudo panels, which are less costly and easy to build with the available data for the firms. Our approach is based on a model-free technique: Dual Multiple Factor Analysis. The synthesis of the multivariate table is visualised on a common space that sheds light on customers' trajectories of satisfaction. A real case study of an Italian bank is illustrated. Results related to the dynamic profiling of the clients highlights highly different behaviours that warn the management of the future trends of the services.

keywords: Customers Profiling, Customer Satisfaction Surveys, Banking Service, Dual Multiple Factor, Pseudo-Panels.

1 Introduction

This paper studies the longitudinal Customer Satisfaction (CS) in order to measure customers' assessment changes for a banking service through a repeated cross-sectional surveys. In order to clarifying the empirical innovation of the proposed approach, first we contextualized the paper into CS literature, then we illustrated advantages of pseudo-panel respect to a classical panel research design, finally, we detailed the characteristics of the technique (Dual Multiple Factor Analysis) applied to a real case of study.

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To date, the study of Customer Satisfaction has dominated marketing behavioural literature (Homburg et al., 2006). Although there are several benefits gained by a company when CS is measured, such practice appears to be less relevant when confined to a cross-sectional perspective. A shift in emphasis from a static to dynamic approach appears to be a worthwhile change (LaBarbera and Mazursky, 1983; Bolton, 1998; Bolton and Lemon, 1999; Baumann et al., 2012; Liberati and Mariani, 2012). Despite the strong recognition that consumer behaviour should be viewed from a dynamic perspective, only a residual percentage of the studies published in marketing have addressed the problem in this manner (Williams and Plouffe, 2007; Rindfleisch et al., 2008). The dearth of panel studies appears to be largely a consequence of costs to the company and difficulty in obtaining longitudinal data sets and/or maintaining the sample over time (Bove and Johnson, 2009; Leonidou et al., 2010), as well as due to little incentive to build databases of historical performance for products and services (Dekimpe and Hanssens, 2000). Cross-sectional surveys are generally preferred over customer panel studies because are the simplest way to collect information from the population existing at a fixed point in time. They are suited to the exploration of behaviours that vary across individuals, whereas gross change or change at an individual level can only be inferred from speculation or qualitative analysis of shifts (Kalton and Citro, 1995). Conversely, panel data is typically the best method of capturing the complexity of consumer dynamics and gaining causal insights. Such sample designs are not free of drawbacks, which can occur in the recruiting phase, producing an invariant sample in different waves; however, changes in the population and panel attrition may cause a bias of estimates (Armstrong and Overton, 1977). Given the deficiencies of cross-sectional data and the problems associated with collecting longitudinal panel data, one practical solution is to exploit, as much as possible, all of the information already available in various cross-sectional data sources Frethey-Bentham (2011). The econometric literature proposes a way to perform such matching: the collection of pseudo-panel data, by means of which it is possible to monitor gross change utilising a time series of cross-sectional data. At this regards, Deaton (1985) introduced the use of cohorts to estimate a fixed effects model from repeated cross-sections. In his approach, individuals sharing some common characteristics (most notably, year of birth) are grouped into cohorts, after which the averages within these cohorts are treated as observations in a pseudo-panel[1] (Masserini et al., 2017). Therefore, the average behaviour of these groups is then tracked over time as long as the sample is continually representative of a population that has a fixed composition (Moffitt, 1993; Collado, 1997; Verbeek and Nijman, 1993). The benefits of such a procedure are several, related to a decrease in attrition, to dropping individual measurement errors and gaining a longitudinal backward view on consumer consumption, even though changes occurring at the micro level of purchase behavioural data are almost too complex to be synthesised[2]. Although the econometric approach has

[1] As argued by Verbeek and Vella (2005) the fixed effect estimator based on the pseudo panel of cohort averages may provide an attractive choice: their Monte Carlo experiment shows that the bias that is present within the estimator for the dynamic model using genuine panel data (Nickell, 1981) is much larger than what is found for similar estimators employed upon cohort aggregates (Verbeek, 2008).

[2] The aggregation inherent in pseudo-panel data must produce cohorts with large sizes and must involve

provided a valuable contribution to studying pseudo panel data, such a model seems inadequate for the treatment of marketing surveys, where individual level changes must be monitored. One radically different way to integrate data is a statistical matching area that has designed several alternative techniques to link datasets together. These methods use two (or more) available data sources (usually samples), referring to the same target population, with the aim of studying the relationship among variables that are not jointly observed in a single data source (D'Orazio et al., 2006). The integration is carried out by means of parametric and nonparametric algorithms aimed to impute missing data (e.g., the Stochastic Regression Imputation or Nearest Neighbours), even though the exact matches are not always available. The usage of matching across time is not straightforward because it requires the invariability of the matching variables over time, the choice of the donor and the recipient file, on which depends the accuracy of the linking process and the assumption of stationarity among periods[3].

In an attempt to approach the Customer Satisfaction study from a dynamic perspective based on pseudo panel surveys, this work proposes the usage of Multiple Factor Analysis (MFA), which is an extension of the Principal Component Analysis (PCA), tailored to handle multiple data tables that measure sets of variables collected during the same observations, or, alternatively, (in the Dual MFA) multiple data tables where the same variables are measured during different sets of observations. One of the purposes of such a method is to find a set of common factor scores (often called compromise factor scores) by which means it is possible to build a (common) projection space where one can visualise communalities and discrepancies among subjects across different waves. The advantages of such a technique are several and range from full information employment (in terms of instances and variables), to synthesising the dimensionality of the tables and easily visualising points across time. Indeed, once all of the instances have been embedded into the common factorial plan, a post-hoc stratification can be performed to reduce the number of entities into a manageable number of groups that are mutually exclusive and share well-defined characteristics. This allows us to draw trajectories of the satisfaction of ideal types so as to adjust a brand's products to the audience and to obtain insights on the expectations and perceptions of client targets.

The rest of the paper is organized as follows: section 2 shows the theoretical foundations of the Multiple Factor Analysis. Section 3 provides a detailed description of data and the research design. Section 4 presents the results, and finally, section 5 proposes some concluding remarks and indicates possible further developments.

2 Multiple Factor Analysis

The analysis of data comprising several sets of individuals described by a same set of variables is a problem frequently encountered, not only in marketing context. The differ-

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the careful choice of cohorts to obtain the largest reduction of heterogeneity within each cohort but at the same time maximise the heterogeneity between them (Moffitt, 1993).

[3] The assumption of stationarity defines the suitable period for matching two samples. If severe changes in variables occur, matching is not the recommended procedure (Ingram et al., 2000).

ent issues raised by the consideration of a partition on the individuals are, for instance, the comparison of different Principal Components Analyses conducted on the same variables in different groups of individuals in a geometrical framework (Krzanowski, 1979) and by the use of hierarchical series of tests (Flury, 1984). Multiple Factor Analysis (MFA) answers exactly such task. Its goal is to analyze several sets of variables collected on the same observations, or - as in its dual version - several sets of observations measured on the same variables (Escofier and Pages, 1988; Escoffier and Pagès, 1990). The technique belongs to bigger Principal Component Analysis family, which comprises related techniques such as multi-block Correspondence Analysis and the joint analysis of tables[4] (Escoufier, 1980; Lavit et al., 1994). The general idea behind the Dual MFA (DMFA) is to normalize each of the variables data sets and then to combine these data tables into a common representation of the variables called the compromise map (Lê and Pagès, 2010). Let's denote with X a $N \times K$ matrix matrix composed by column-wise juxtaposition of L sub-matrices, each of them collecting information on the same set of variables but different observations

$$X = \begin{bmatrix} X_{[1]} \\ X_{[2]} \\ . \\ X_{[\ell]} \\ . \\ . \\ X_{[L]} \end{bmatrix} \rightarrow X_{[\ell]} = \begin{bmatrix} x_{11} & . & .x_{1k} & . & .x_{1K} \\ . & & & & \\ . & & & & \\ . & & & & \\ x_{N_\ell 1} & . & .x_{N_\ell k} & . & .x_{N_\ell K} \end{bmatrix} \tag{1}$$

According to that, each table $X_{[\ell]}$ ($\ell = 1, 2, ...L$) is a $N_{[\ell]} \times K$ data matrix so that $\sum_{\ell=1}^{L} N_{[\ell]} = N$. Let p_i^ℓ ($i = 1, ..j, ..N_\ell$) be the weight (mass)[5] assigned to each instance i belonging to the sub-matrix ℓ, and let's denote with D the ($N \times N$) diagonal matrix (metric) whose terms are the masses associated to the observations. The total variability of X could be studied by means of Principal Component Analysis performed on the entire table, taking into account in the interpretation of each axis the partition on the individuals into different groups (waves). Although this approach allows visualizing the variables' correlations based on the total instances, it does not consider that such correlations are not necessary the same from one group of individuals to another. The comparison of the correlations among variables would be facilitated by means of a simultaneous representation defined for each group of individuals which is one the aims of DMFA (Abdi et al., 2013). This purpose can be pursued performing a preprocessing step in order to center and normalize the variables by group. For representing the total variability of X, it has to be identified the directions of inertia to which different groups

[4]The joint Analysis of tables is called ACT which stands for the French expression Analyse Conjointe de Tableaux also called as STATIS Structuration des Tableaux à Trois Indices de la Statistique (des Plantes, 1976).

[5]Masses are non-negative elements whose sum equals to 1. If the elements have the same weight they are chosen equal to $p_i^\ell = 1/N_\ell$

contribute: a balance of the distribution of the variance within groups is the pivotal point[6]. Consequently, Pagès (2016) proposes to weight each variable belonging to $X_{[\ell]}$ with $1/\lambda_1^\ell$, where λ_1^ℓ is the first eigenvalue of the separate PCA for the group ℓ[7]. Such weight induces a specific metric in the individuals' space $\mathbb{R}^K$ where the distance between each point i from the origin 0 is obtained as direct sum of the squared distance between the origin and the projection of i on the subspace generated by each group.

$$d(0,i) = \sum_{\ell=1}^{L} \frac{1}{\lambda_1^\ell} \sum_{k=1}^{K} x_{ik\ell}^2 = \sum_{\ell=1}^{L} d(0, i^\ell) \tag{2}$$

The property holds also for the variables, therefore, the cloud of subjects (N), projected onto the subspace generated by a variable k, can be made up by summing the clouds N_ℓ^k. The clouds of variables and subjects are linked by relationships of duality (or transition). According to such framework, it is possible to analyze $L+1$ clouds of individuals: the projection of the L sub-matrices in a common space and the one associated with the whole set of active data (mean cloud). The comparison of partial clouds is the geometric interpretation of the question of whether two individuals i and j which are similar in terms of group ℓ. The mathematical formulation of DMFA can be translated into the algebraic representation into two steps. In the first one a grand matrix $\tilde{X}$ is obtained, juxtapositioning the standardized $X_{[l]}$ by column and using as weighting the first eigenvalue coming from separate PCAs on $X_{[\ell]}$.

$$\tilde{X} = \begin{bmatrix} \tilde{X}_{[1]} \\ \tilde{X}_{[2]} \\ . \\ \tilde{X}_{[\ell]} \\ . \\ . \\ \tilde{X}_{[L]} \end{bmatrix} \rightarrow \tilde{X}'_{[\ell]} = \underbrace{\begin{bmatrix} \sqrt{\frac{1}{\lambda_1^\ell}} & 0 & 0 & . & . & . & 0 \\ 0 & \sqrt{\frac{1}{\lambda_1^\ell}} & 0 & . & . & . & 0 \\ . & . & . & . & . & . & .. \\ 0 & . & . & \sqrt{\frac{1}{\lambda_1^\ell}} & . & . & 0 \\ . & . & . & . & . & . & .. \\ 0 & . & . & . & . & . & \sqrt{\frac{1}{\lambda_1^\ell}} \end{bmatrix}}_{\triangle^l} \cdot \underbrace{\begin{bmatrix} x_{11} & . & . & . x_{N_\ell 1} \\ x_{12} & . & . & . x_{N_\ell 2} \\ . & & & \\ . & & & \\ x_{1K} & . & . & x_{N_\ell K} \end{bmatrix}}_{X'_{[\ell]}} \tag{3}$$

where $X'_{[\ell]}$ is the transpose matrix of the correspondent $X_{[\ell]}$. In the second step, we performed a Principal Component Analysis of the grand matrix.

$$(\tilde{X}' D \tilde{X}) = \Lambda \Gamma \Lambda' \tag{4}$$

where Γ is an orthonormal basis of $K \times K$ dimension and Λ is a $K \times K$ diagonal matrix of eigenvalues. The spectral theorem decomposition ensures the best reconstruction in

[6]The contribution of a group is harmonized directly rather than indirectly providing an upper limit to the contribution of a group in constructing an axis.

[7]The usage as a weighting of the standardized maximal axial inertia coming from separate PCAs improves the interpretation of MFA results because it helps to individuate more important descriptors of the factor axis. It is the same idea applied in Multiple Correspondence Analysis.

terms of least square of the weighted correlation matrix $(\tilde{X}' D\tilde{X})$; the solution provides individuals' factor scores of the total matrix X, which represent a compromise of the K sub-matrices.

$$F = X \triangle^2 U \tag{5}$$

Since the PCA is performed on a correlation matrix the coordinate of a generic variable k on the compromise axis of rank s is computed as correlation coefficient between the variables k and the factor s $r(x_k, F_s)$. Similarly, the variables' coordinates for each waves can be easy carried out substituting x_k with x_k^l into the correlation coefficient.

It is also interesting to study the sets of variables globally, in order to uncover if different sets induce similar structures on the individuals. As exposed in this section, each group of individuals is represented by a different correlation matrix $C_\ell = X'_\ell D_\ell X_\ell$ that can be considered as vectors in $\mathbb{R}^{K^2}$. In order to study the global similarities among clouds of individuals we can compute the R_V coefficient introduced by Escoufier (1973) which can be interpreted as a coefficient of correlation between two matrices.

$$R_V = \frac{trace[C_\ell C_{\ell'}]}{\sqrt{trace[C_\ell C_\ell] \times trace[C_{\ell'} C_{\ell'}]}} \tag{6}$$

The coefficient ranges between 0-1 and represents a normed measure of similarity between two configurations. A graphical representation of such dissimilarities is obtained by means of DMFA projecting the correlation matrix C_ℓ on the axis $U = u'_s u_s$ induced by the axis u_s obtained with the compromise solution.

3 Data and Research Design

Data analysed in this study aims to monitor several aspects related to CS. It collects clients' appreciations about: banking touch points, imagine of the credit institute and a proxy of customers engagement across three years (2010-2012). The choice of monitoring such dimensions lies of the fact that they explore the interactions about bank and retail customers as well as their perceptions about critical attributes which differentiate the bank from the others present in the Italian market. The potential population was very large in every wave (Tab. 1).

Table 1: Sizes sample per year and touch point used

	Year		
	2010	2011	2012
Original Size Sample	9144	10055	12001
Agency (A)	8419	8988	10993
ATM (B)	6952	8021	9244
Internet Banking (C)	2840	3454	4150
All services (A+B+C)	2068	2058	2067

In order to assess overall Customer Satisfaction as well as the appreciation for each channel, we selected only those clients who experienced each service at least twice per year, although this choice decreased the sample size dramatically. Hence, the total number of instances was 6193, summarizing, respectively, the 2068 (2010), 2058 (2011), 2067 (2012) observations over three years (Tab. 1). Unfortunately, no information about the personal identity of respondents was recorded. On each occasion, customers were interviewed using the same questionnaire with a CATI (Computer Assisted Telephone Interviewing) system. For each specific item, as well as for overall satisfaction, respondents expressed assessments on a ten-point Likert scale (Tab. 2).

Table 2: Descriptive statistics (mean standard deviation and quartiles) for each items per waves.

2010	Mean	Std. Dev.	Q_1	Q_2	Q_3
a. Satisfaction for the banking personnel	7.980	1.610	7	8	9
b. Satisfaction for the banking ATM	8.200	1.359	7	8	9
c. Satisfaction for the internet banking service	8.290	1.342	8	8	9
d. Probability to recommend the bank to someone	7.120	2.245	6	8	8
e. Prestige	7.580	1.714	7	8	9
f. Innovation	6.850	1.868	6	7	8
g. Honesty	7.360	1.786	6	8	8
h. Trust	7.600	1.857	7	8	9
i. Bank's attention to the customers	6.750	2.106	6	7	8
l. Overall Satisfaction	7.550	1.528	7	8	8
2011					
a. Satisfaction for the banking personnel	7.970	1.658	7	8	9
b. Satisfaction for the banking ATM	8.170	1.409	7	8	9
c. Satisfaction for the internet banking service	8.290	1.323	8	8	9
d. Probability to recommend the bank to someone	7.520	1.562	7	8	8
e. Prestige	7.570	1.696	7	8	9
f. Innovation	6.850	1.912	6	7	8
g. Honesty	7.390	1.787	6	8	8
h. Trust	7.650	1.813	7	8	9
i. Bank's attention to the customers	6.780	2.167	6	7	8
l. Overall Satisfaction	7.200	2.173	6	7	9
2012					
a. Satisfaction for the banking personnel	8.090	1.574	7	8	9
b. Satisfaction for the banking ATM	8.080	1.552	7	8	9
c. Satisfaction for the internet banking service	8.490	1.260	8	9	10
d. Probability to recommend the bank to someone	7.750	1.522	7	8	9
e. Prestige	7.680	1.739	7	8	9
f. Innovation	7.300	1.975	6	7	8
g. Honesty	7.690	1.712	7	8	9
h. Trust	7.730	1.854	7	8	9
i. Bank's attention to the customers	7.000	2.132	6	7	8
l. Overall Satisfaction	7.390	2.206	6	8	9

A preliminary analysis of the descriptive statistics in Table 2 show a seesaw trend of satisfaction related to items as personnel and internet banking during the period from

2010-2012. Although we registered the variation of slope across time, the appreciation of the customers regarding banking personnel (a) seems to be almost constant and growing for word of mouth (d) and honesty (h). On the contrary, clients show a decreasing satisfaction for automatic teller machines (b) across the years; in this case, the substitution of the old machines with more advanced ones interrupted the decline in the assessment. An inspection of the rest of the indicators highlights interesting behaviours for all aspects related to the image of the credit institute. According with the market, sample customers seem to prefer receiving assistance on-line instead of presenting themselves at banking branches.

Additionally, it is easy to detect a possible disaffection for the bank, indicated by a drop in overall satisfaction for the clients from 2010-2011. Despite the fact that this tendency is worrisome, especially if it lasts for a long period of time, it must be reviewed from a global economic perspective. The peculiarity of the period under examination, in fact, is affected by a general detachment with regard to banks due to the huge financial crisis that involved most of the Western economy with severe social consequences. Finally, the distribution of the preferences shows concentration of moderate to high levels of assessments, highlighting a clear negative skewness in all the monitored items. In regard to the distribution of gender per wave, the prevalence of males must be addressed, as it remains constant over the years. The subjects interviewed are mostly aged from 25-54, generally show low and medium education qualifications. (Tab. 3) .

Table 3: Percentage distributions of socio-demographics classes across 2010-2012

Variables		2010	2011	2012
Gender	Male	56.60%	55.80%	55.70%
	Female	43.40%	44.20%	44.30%
	TOT	100%	100%	100.0%
Age	18-24	4.10%	4.40%	4.10%
	25-34	18.80%	19.00%	18.80%
	35-44	34.20%	33.50%	33.40%
	45-54	23.10%	23.40%	22.40%
	55-64	14.60%	14.40%	16.10%
	65-74	5.30%	5.40%	5.20%
	TOT	100%	100%	100%
Education	Degree (D)	30.10%	29.90%	30.80%
	High School (HS)	55.80%	55.90%	54.80%
	Middle School (MS)	13.50%	13.40%	13.40%
	Elementary School (ES)	0.60%	0.80%	1.00%
Tot	TOT	100%	100%	100%

Regarding the Overall Satisfaction (Tab. 4), women are more satisfied then men over time, and the 2011 is the year whose the highest level of gender difference is detected. Extreme ages classes show higher appreciation for the bank service respect to the other classes, although such trends might be effected by the heterogeneity of these small groups' size. In particular, in the first wave (2010) the lowest assessment is given

Table 4: Average values of Overall Satisfaction per socio-demographics classes across 2010-2012

Variables		2010	2011	2012
Gender	Male (M)	7.428	7.357	7.599
	Female (F)	7.710	7.735	7.942
Age	18-24	8.083	7.956	7.882
	25-34	7.652	7.481	7.644
	35-44	7.494	7.502	7.776
	45-54	7.519	7.476	7.659
	55-64	7.412	7.574	7.864
	65-74	7.664	7.541	7.925
Education	Degree (D)	7.280	7.393	7.527
	High School (HS)	7.603	7.525	7.788
	Middle School (MS)	7.871	7.797	8.065
	Elementary School (ES)	8.923	7.813	8.391

by the customers aged 55-64, then by the customers aged 44-54 and those aged 25-34 in the second and third waves respectively, despite the baseline level of satisfaction is never less than 7. That affects also the interpretation of the empirical evidences: observed differences in terms of evaluations are interpreted as relevant changes because respondents use only upscale levels of the Likert scale 1-10.

Moreover, the more customers were educated, the more disaffection they show towards the bank. Visual inspection of the table 4 highlights that highest appreciation is given by poor educated classes, on the contrary, those with diploma or with degree show certainly lower levels of satisfaction.

4 Results

In this section, we present the results of our approach and discuss the main business implications. For the sake of clarity, we have divided the results into two subsections: one dedicated to the compromise plane and its characterisation and the other dedicated to the dynamic segmentation of the customers.

4.1 The Compromise Plan: Statistical Measures and Interpretations

As illustrated in section 3, our data matrix X (6193×10) was obtained by summing up (by column) three different data tables $X = [X_1; X_2; X_3]$ with the same variables collected from different individuals in the same target population. A first check on the data was run to test if X_1, X_2, X_3 and X follow a multivariate normal distribution. A violation of such an assumption would make inapplicable of Kamakura and Wedel (2000) that is based on a Factor Model with Maximum Likelihood estimates obtained by multivariate normal data. As expected, our data tables do not show a sufficient probability agreement with such a distribution (see the Appendix for detailed statistical

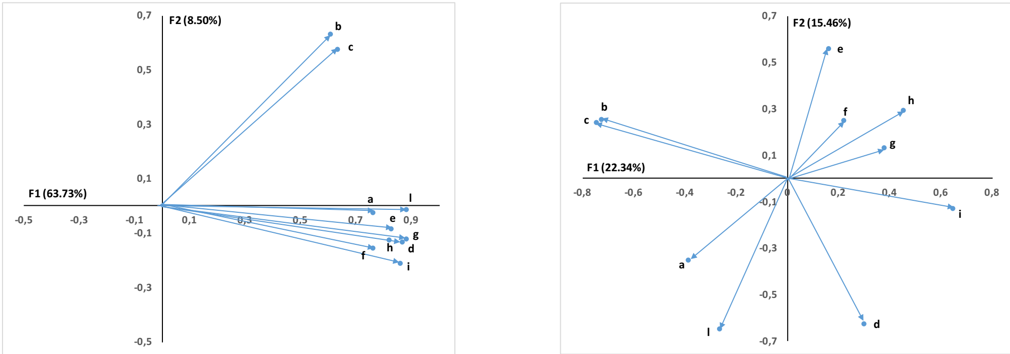

Figure 1: Variables projection onto the principal plane: left panel) normalized items; right panel) double-centered items

tests); therefore, the data fusion process was realised with the Dual-MFA, which is model free. The two-step procedure, outlined in section 2, was employed on the matrices under study: first, X_1, X_2, X_3 were centered and standardised and a separate PCA was run on each of the tables to obtain the weights to balance the within-groups inertia (Tab 6 in Appendix). Then, a PCA was performed on the grand matrix obtained, as illustrated in equation 3. The solution provided by the spectral decomposition (eq. 4) uncovers a peculiar configuration of the points onto the principal compromise plane (Fig. 1).

The first factor axis is positively correlated with all of the variables under study: this occurs when subjects give same assessments to all the monitored items. The mathematical translation of such behaviour is evident in the first eigenvalue that becomes approximately a linear function of the average correlation among the variables (Friedman and Weisberg, 1981). In a statistical perspective this is known as size effect (Pagès, 2016) and it induces that the first principal component is interpreted as general average of the measurements. In order to highlight the main differences among years but also the inter-individual differences within each year, we double-centered the tables, once subtracting the individual mean from the items and then normalizing the whole table (Abdi et al., 2013; Baron, 1996).

In figure 1, a new scatter of variable coordinates is displayed. On the factor 1, it is easy to notice a contrast among the appreciations for a standardized customer assistance (ATM and on-line banking) vs a banking service designed on clients' needs (Bank's attention to the customers). On the other hand, factor 2 discloses a dichotomy among variables that synthesise the satisfaction for the bank image (prestige, innovation, honesty and trust) and variables that describe experience with the bank. Consequently, we named f_1 as *standardized-customised banking service* and f_2 as *imagined-experienced bank.*

The detected configuration is not due to the technique applied, which perfectly summarises the trends and characteristics of the partial clouds (see Table 7 in Appendix), but instead, it is a consolidated behaviour of the clients interviewed. Further evidence for this conclusion comes from the R_V coefficient matrix (Tab. 5) which shows high similarities in information structures from 2010-2012; this confirms a lack of shocks in the variables monitored and stable trends over the three years.

Table 5: R_V coefficient values across the four waves

	2010	2011	2012
2010	1	0.994	0.987
2011	0.994	1	0.985
2012	0.987	0.985	1

Therefore, the subspace in figure 1 allows to investigate customer behaviours over time.

4.2 Customer Satisfaction Assessment: the Dynamic Behaviors

Instances can also be projected on the compromise plane. Due to the large number of individuals comprising the sample, it is very difficult to visualise the dynamic paths of each subject even in a panel case; therefore, a segmentation was performed to profile the long-term behaviours of the ideal types. We focus our attention on some groups but the analysis can easily be replicated for any other instance. We compare the trajectories of clients distinguished by socio-demographic characteristics, because, generally, such variables play an important role in the assessment formulation. Visual inspection of the graphical representations in figures 2-3, which depict average positions and inner variability of the profiles over time[8], reveals different evolutions of the monitored groups.

In our case, female customers moves along the positive side of the first axis, showing a high appreciation for a customised banking service (Fig. 2). On the contrary, males move exactly on the opposite direction, seeming more involved with a standardised assistance. Also the relationship with the bank has different connotations when studied by gender: females prefer to experience services provided by the financial institution while males take in high consideration the bank's image. Both tendency paths highlight an involution in the temporal trends, probably underling a lack of specific actions/stimuli per gender. Although the two groups' evolutions are characterised by relevant variability - proportional to the groups' size and to the dispersion of the data values - the difference of behaviour by gender is significative at 95% of probability for almost all years (Tab. 9 in Appendix).

A second comparison has been performed that contrasts customers' behaviours distinguished by different educational levels (Fig. 2). This time, trajectories appear different

[8]The inner (or within) deviance of each group g in each year ℓ has been computed as:

$$WD_{\ell g} = \sum_{s}^{2}\sum_{i}^{n_g}(f_{si} - \bar{f}_{sg})^2 \tag{7}$$

where f_{si} is the coordinate of the i-th point onto the s-th factor and $\bar{f}_{sg}$ is the s-th axis mean relatives to the group g. $WD_{\ell g}$ measures the variability of the profiles in each time points (Tab. 9-11 in Appendix) and provides a dimension indicator of the bubbles sizes of the figures 2-3

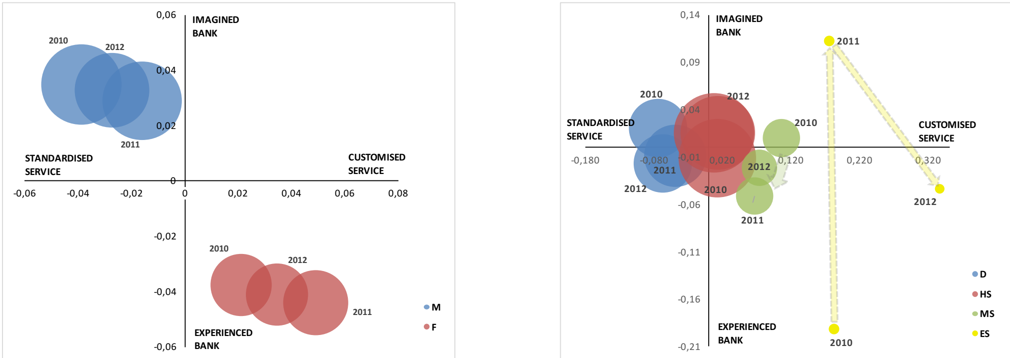

Figure 2: Dynamic behaviours: left panel) trajectories per gender; right panel) trajectories per educational levels

for shapes and lengths. Graduates, lying on the negative side of the first axis over the three years, show a high appreciation for remote touch points while middle school graduates have more fuzzy evaluations. On the contrary, poorly educated profiles (as middle school or elementary school graduates) seem to prefer customised assistance. Such evidences are statistically significant at an alpha level of 0.10 (Tab. 10 in Appendix); whereas those that investigate the type of relationship among different educational classes and the bank do not highlight any differences for any significant level.

Educational level seems to have an effect in bank's dynamic assessment not only in terms of service choice but also in terms of reaction to stimuli or to events connected to economic/financial environment. This is easy to recognize in the bubble plot: customers with a degree or a high school diploma are more static while the others show longer paths over the same time span [9].

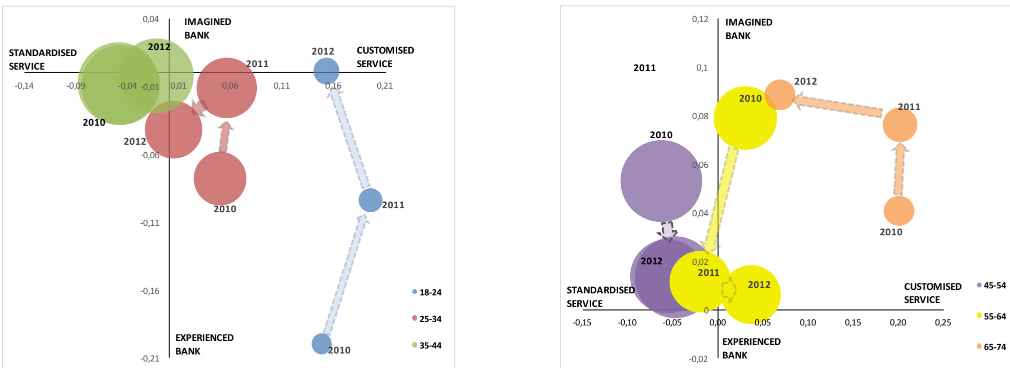

Figure 3: Dynamic behaviours: left panel) trajectories per age classes 18-44; right panel) trajectories per age classes 45-74

[9]Obviously, all the considerations relatives to poor educated classes have to take into account the reduced sizes of such groups. That might influence the heterogeneity of the observed behaviours and consequently their trajectories.

Finally, bank's customers have been segmented according to age classes in order to compare and contrast possible similarities and/or differences. Due to the relevant number of the age groups selected in the study, the graphical representation of the trajectories is produced with two pictures for a better visualisation of the trends (Fig. 3). As expected, clients' paths are mainly clustered respect to the first principal component, but the depicted configuration highlights very peculiar behaviours. The extreme age classes (as 18-24 and 65-74) shift along the positive side of the first axis, while the central ones (as 35-44 and 45-54) lie on the opposite side of the axis. Therefore, mature age clients (but not old) seem to prefer a fast banking assistance, without personal contact. The others, generally, show a considerable appreciation for a customised service. Such tendencies are further confirmed (at alpha level of 0.10) by the results of the analysis of variance collected in table 11 in Appendix; the type of relation between customers and credit institute, again, is not statistically significant. Once more, the observed paths could be distinguished by variability and length of the trajectories: mature age clients make little shifts on the compromise plane, showing a resistant attitude to any stimuli from the bank. On the contrary, very old and very young profiles, characterised by high similarity in behaviours, cover longer distances, highlighting a relevant subjection to the management actions.

5 Conclusions

This paper presents a new way of approaching Customer Satisfaction management. The idea originated from the necessity of a longitudinal perspective in assessments of Customer Satisfaction, also expressed in several contributions in behavioral studies. Today, this task is even more important because information is available and inexpensive. For such reasons, the fusion of cross-sectional surveys seems to be a good strategy for obtaining knowledge from clients and is useful in addressing management decisions. Of course, modelling pseudo-panels must account for a decrease in sample variance due to the cohort-building process or due to the discharge of units in the case of matching. The proposed method is not affected by either of these problems because it can manage different data tables collected at different time points. In fact, the three-way factor analysis provides a unique space for compromise in which all of the instances are plotted and can be segmented over time. The strength of this approach is that it is model-free, so it can be applied to every data table's comparison/visualisation.

In reference to the real case study illustrated in the paper, the evidence found is truly interesting and can easily be interpreted in terms of management implications. The compromise factorial plane obtained allows to distinguish the clients profiles who prefer remote services from those who are involved with a customised assistance. It also uncovers differences in type of relationship between customers and bank: such evidences, if monitored over time, can help management to better respond to clients' demands.

The study also highlights important warnings concerning clients' preferences: gender, education, and age class are influencing factors in shifting the Customer Satisfaction for a specific service. Therefore, management decisions regarding touch points or remote services must take into account the modifications made in recent years that can effect future perceptions.

An important direction for future research could be a comparison of the results from the panel and pseudo-panel data to uncover possible differences in behaviour between segments.

References

Abdi, H., Williams, L. J., and Valentin, D. (2013). Multiple factor analysis: principal component analysis for multitable and multiblock data sets. *Wiley Interdisciplinary reviews: computational statistics*, 5(2):149–179.

Armstrong, J. S. and Overton, T. S. (1977). Estimating nonresponse bias in mail surveys. *Journal of marketing research*, pages 396–402.

Baron, H. (1996). Strengths and limitations of ipsative measurement. *Journal of Occupational and Organizational Psychology*, 69(1):49–56.

Baumann, C., Elliott, G., and Burton, S. (2012). Modeling customer satisfaction and loyalty: survey data versus data mining. *Journal of services marketing*, 26(3):148–157.

Bolton, R. N. (1998). A dynamic model of the duration of the customer's relationship with a continuous service provider: The role of satisfaction. *Marketing science*, 17(1):45–65.

Bolton, R. N. and Lemon, K. N. (1999). A dynamic model of customers' usage of services: Usage as an antecedent and consequence of satisfaction. *Journal of marketing research*, pages 171–186.

Bove, L. L. and Johnson, L. W. (2009). Does true personal or service loyalty last? a longitudinal study. *Journal of Services Marketing*, 23(3):187–194.

Collado, M. D. (1997). Estimating dynamic models from time series of independent cross-sections. *Journal of Econometrics*, 82(1):37–62.

Deaton, A. (1985). Panel data from time series of cross-sections. *Journal of econometrics*, 30(1-2):109–126.

Dekimpe, M. G. and Hanssens, D. M. (2000). Time-series models in marketing:: Past, present and future. *International journal of research in marketing*, 17(2):183–193.

des Plantes, H. L. (1976). *Structuration des tableaux à trois indices de la statistique: théorie et application d'une méthode d'analyse conjointe*. PhD thesis, Université des sciences et techniques du Languedoc.

D'Orazio, M., Di Zio, M., and Scanu, M. (2006). *Statistical matching: Theory and practice*. John Wiley & Sons.

Escoffier, B. and Pagès, J. (1990). Simple and multiple factor analyses. objectives, methods and interpretation (in french).

Escofier, B. and Pages, J. (1988). Analyses factorielles simples et multiples: Objectifs, méthodes. *Interprétation*.

Escoufier, Y. (1973). Le traitement des variables vectorielles. *Biometrics*, pages 751–760.

Escoufier, Y. (1980). Lanalyse conjointe de plusieurs matrices de données. *Biométrie et temps*, 58:59–76.

Flury, B. N. (1984). Common principal components in k groups. *Journal of the American Statistical Association*, 79(388):892–898.

Frethey-Bentham, C. (2011). Pseudo panels as an alternative study design. *Australasian Marketing Journal (AMJ)*, 19(4):281–292.

Friedman, S. and Weisberg, H. F. (1981). Interpreting the first eigenvalue of a correlation matrix. *Educational and Psychological Measurement*, 41(1):11–21.

Henze, N. and Zirkler, B. (1990). A class of invariant consistent tests for multivariate normality. *Communications in Statistics-Theory and Methods*, 19(10):3595–3617.

Homburg, C., Koschate, N., and Hoyer, W. D. (2006). The role of cognition and affect in the formation of customer satisfaction: a dynamic perspective. *Journal of Marketing*, 70(3):21–31.

Ingram, D. D., OHare, J., Scheuren, F., and Turek, J. (2000). Statistical matching: A new validation case study. In *Proceedings of the Survey Research Methods Section, American Statistical Association*, pages 746–751.

Kalton, G. and Citro, C. F. (1995). Panel surveys: Adding the fourth dimension. *Innovation: The European Journal of Social Science Research*, 8(1):25–39.

Kamakura, W. A. and Wedel, M. (2000). Factor analysis and missing data. *Journal of Marketing Research*, 37(4):490–498.

Krzanowski, W. (1979). Between-groups comparison of principal components. *Journal of the American Statistical Association*, 74(367):703–707.

LaBarbera, P. A. and Mazursky, D. (1983). A longitudinal assessment of consumer satisfaction/dissatisfaction: the dynamic aspect of the cognitive process. *Journal of marketing research*, pages 393–404.

Lavit, C., Escoufier, Y., Sabatier, R., and Traissac, P. (1994). The act (statis method). *Computational Statistics & Data Analysis*, 18(1):97–119.

Lê, S. and Pagès, J. (2010). Dmfa: Dual multiple factor analysis. *Communications in StatisticsTheory and Methods*, 39(3):483–492.

Leonidou, L. C., Barnes, B. R., Spyropoulou, S., and Katsikeas, C. S. (2010). Assessing the contribution of leading mainstream marketing journals to the international marketing discipline. *International Marketing Review*, 27(5):491–518.

Liberati, C. and Mariani, P. (2012). Banking customer satisfaction evaluation: a three-way factor perspective. *Advances in Data Analysis and Classification*, 6(4):323–336.

Mardia, K. V. and Foster, K. (1983). Omnibus tests of multinormality based on skewness and kurtosis. *Communications in Statistics-theory and methods*, 12(2):207–221.

Masserini, L., Liberati, C., and Mariani, P. (2017). Quality service in banking: a longitudinal approach. *Quality & Quantity*, 51(2):509–523.

Moffitt, R. (1993). Identification and estimation of dynamic models with a time series of repeated cross-sections. *Journal of Econometrics*, 59(1-2):99–123.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica: Journal of the Econometric Society*, pages 1417–1426.

Pagès, J. (2016). *Multiple factor analysis by example using R*. CRC Press.

Rindfleisch, A., Malter, A. J., Ganesan, S., and Moorman, C. (2008). Cross-sectional versus longitudinal survey research: Concepts, findings, and guidelines. *Journal of Marketing Research*, 45(3):261–279.

Verbeek, M. (2008). Pseudo-panels and repeated cross-sections. *the econometrics of* *panel data*, pages 369–383.

Verbeek, M. and Nijman, T. (1993). Minimum mse estimation of a regression model with fixed effects from a series of cross-sections. *Journal of Econometrics*, 59(1-2):125–136.

Verbeek, M. and Vella, F. (2005). Estimating dynamic models from repeated cross-sections. *Journal of econometrics*, 127(1):83–102.

Villasenor Alva, J. A. and Estrada, E. G. (2009). A generalization of shapiro–wilk's test for multivariate normality. *Communications in StatisticsTheory and Methods*, 38(11):1870–1883.

Wang, C.-C. (2015). A matlab package for multivariate normality test. *Journal of Statistical Computation and Simulation*, 85(1):166–188.

Williams, B. C. and Plouffe, C. R. (2007). Assessing the evolution of sales knowledge: A 20-year content analysis. *Industrial Marketing Management*, 36(4):408–419.

6 Appendix

Table 6: First eigenvalue from sperate PCA

λ_1^ℓ	Value	$1/\sqrt{\lambda_1^\ell}$
λ_1^1	6.423	0.395
λ_1^2	6.439	0.394
λ_1^3	6.270	0.399

Table 7: Variables coordinates on the principal factor plane from separate PCAs

	2010		2011		2012	
	f_1	f_2	f_1	f_2	f_1	f_2
a	-0.404	-0.340	-0.344	-0.345	-0.401	-0.391
b	-0.740	0.215	-0.730	0.259	-0.689	0.278
c	-0.727	0.232	-0.727	0.280	-0.767	0.191
d	0.257	-0.648	0.308	-0.671	0.353	-0.554
e	0.136	0.573	0.127	0.566	0.242	0.521
f	0.211	0.281	0.231	0.218	0.234	0.239
g	0.418	0.156	0.360	0.117	0.367	0.104
h	0.469	0.293	0.428	0.294	0.485	0.272
i	0.657	-0.135	0.659	-0.148	0.640	-0.116
l	-0.271	-0.657	-0.253	-0.642	-0.255	-0.655

Table 8: Multivariate Normality test values and relatives p-values

	2010		2011		2012	
MN test	Test Stats	p-values	Test Stats	p-values	Test Stats	p-values
MO	8110.850	0.000	7305.160	0.000	7373.610	0.000
HZ	8272	0.000	8232	0.000	8268	0.000
W*	0.929	0.000	0.932	0.000	0.935	0.000

Legend: MO: test of Mardia and Foster (Mardia and Foster, 1983). HZ: test of Henze and Zirkler (Henze and Zirkler, 1990). W*: test of Villasenor Alva and González Estrada (Villasenor Alva and Estrada, 2009). Fuller details on test calculations and specifications in Wang (2015)

Table 9: Results of the ANOVA related to gender per year

	2010			2011			2012		
F_1	SS	$F_{1,2066}$	p-value	SS	$F_{1,2056}$	p-value	SS	$F_{1,2065}$	p-value
Between Groups	0.699	1.596	0.207	3.906	8.53	0.004	1.953	4.561	0.033
-Within M	560.951			546.040			530.644		
-Within F	343.808			395.408			353.763		
Within Groups	904.759			941.448			884.407		
Total	905.457			945.354			886.360		
F_2	SS	$F_{1,2066}$	p-value	SS	$F_{1,2056}$	p-value	SS	$F_{1,2065}$	p-value
Between Groups	2.243	7.262	0.007	3.159	9.213	0.002	2.779	10.516	0.001
-Within M	395.658			437.052			305.608		
-Within F	242.501			267.871			240.121		
Within Groups	638.159			704.923			545.729		
Total	640.402			708.082			548.508		

Table 10: Results of the ANOVA related to education levels per years

	2010			2011			2012		
F_1	SS	$F_{3,2064}$	p-value	SS	$F_{3,2054}$	p-value	SS	$F_{3,2063}$	p-value
Between Groups	7.13	5.46	0.001	3.253	2.364	0.069	7.116	5.565	0.001
-Within D	278.482			310.893			298.943		
-Within HS	494.080			499.314			465.999		
-Within MS	116.783			122.473			105.509		
-Within ES	8.983			9.421			8.792		
Within Groups	898.328			942.101			879.245		
Total	905.457			945.354			886.360		
F_2	SS	$F_{3,2064}$	p-value	SS	$F_{3,2054}$	p-value	SS	$F_{3,2063}$	p-value
Between Groups	0.916	0.985	0.399	1.239	1.201	0.308	0.639	0.802	0.493
-Within D	198.241			226.189			175.318		
-Within HS	351.717			395.832			295.849		
-Within MS	83.133			77.753			71.223		
-Within ES	6.395			7.068			5.479		
Within Groups	639.486			706.843			547.870		
Total	640.402			708.082			548.508		

Table 11: Results of the ANOVA related to age classes per years

	2010			2011			2012		
F_1	SS	$F_{5,2062}$	Sig.	SS	$F_{5,2052}$	Sig.	SS	$F_{5,2061}$	Sig.
Between Groups	10.923	5.036	0.000	12.036	5.293	0.000	4.476	2.092	0.064
-Within 18-24	17.891			28.000			44.094		
-Within 25-34	161.016			177.330			167.558		
-Within 35-44	313.087			335.994			291.022		
-Within 45-54	241.524			233.329			211.652		
-Within 55-64	125.235			121.331			132.283		
-Within 65-74	35.781			37.333			35.275		
Within Groups	894.534			933.318			881.885		
Total	905.457			945.354			886.360		
F_2	SS	$F_{5,2062}$	Sig.	SS	$F_{5,2052}$	Sig.	SS	$F_{5,2061}$	Sig.
Between Groups	9.152	5.979	0.000	1.661	0.965	0.438	1.615	1.218	0.298
-Within 18-24	18.937			21.193			16.407		
-Within 25-34	82.062			134.220			114.847		
-Within 35-44	227.25			240.183			191.412		
-Within 45-54	164.125			169.541			125.785		
-Within 55-64	119.937			105.963			76.565		
-Within 65-74	18.937			35.321			21.876		
Within Groups	631.250			706.421			546.893		
Total	640.402			708.082			548.508		