COMBINING PLS PATH MODELING AND QUANTILE REGRESSION FOR THE EVALUATION OF CUSTOMER SATISFACTION

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Abstract *Customer satisfaction is a concept that cannot be directly measured because it is a complex concept related to mental constructions. Different factors influence the customer satisfaction and for each of them it is possible to find a set of indicators. Partial Least Squares path modeling is one of the most widespread approaches to estimate the unobservable factors of a customer satisfaction model. Such a method is based on simple and multiple ordinary least squares regressions and it provides a unique system of weights representing the average effect. An innovative approach to Partial Least Squares path modelling based on the introduction of quantile regression in the estimation phases can provide useful benefits to the customer satisfaction evaluation. As quantile regression models the whole distribution of the dependent variable, it is able to measure the role played by factors and indicators at different quantiles of the customer satisfaction. The potentialities of the proposal are introduced through an empirical analysis for the evaluation of the American Customer Satisfaction Index*

Keywords: *PLS path modeling, quantile regression, customer satisfaction.*

1. INTRODUCTION

Customer Satisfaction (CS) is a multidimensional concept which cannot be captured by a single indicator/variable so that it is necessary to resort both to measurable factors (known for example as observable indicators or manifest variables) and factors not directly measurable (known for example as latent factors or variables). Complexity inside CS measurement is often studied planning a causality network (conceptual model) among latent variables (LVs) each measured by a set of manifest variables (MVs).

Partial Least Squares path modeling (PLSPM) (Esposito Vinzi et al., 2010; Tenenhaus, 1998; Vittadini et al., 2007; Wold, 1985) represents a widespread methodological solution for the CS evaluation alternative to the classical covariance-based approach to Structural Equation Models (CBSEM) (Jöreskog, 1970). In

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particular, PLSPM establishes its role in the international scientific literature as a soft modeling approach alternative to the CBSEM because it does not require restrictive distribution hypotheses and huge samples. This is a very interesting feature especially in those application fields where such assumptions are not tenable, at least in full. On the other side, the classical parametric inferential framework cannot be applied and resampling methods are required to obtain empirical confidence intervals and hypothesis testing. The idea behind the model is to measure the LVs through the MVs and to describe the dependence relationships among the linked LVs as well as MVs and LVs.

Several contributes in literature compare CBSEM and PLSPM (among many see (Hair et al., 2012; Rigdon, 2012; Vittadini et al., 2007)) highlighting limitations, advantages and similarities. This paper aims to propose the use of a new robust methodology for the analysis and construction of composite indicators in the CS framework. The method, named Quantile Composite-based Path Modeling (QCPM) (Davino and Esposito Vinzi, 2014, 2016), overcomes a notable limitation of CBSEM and PLSPM: they are based on the estimation of average effects. Such an issue is a very important limiting factor in the CS evaluation where it is interesting to consider effects (in sign and strength) on the extreme parts of the satisfaction distribution. In essence, a challenge of the current state of the art in the CS evaluation is that the complexity behind a CS index is badly caught by the traditional methods proposed in literature which limit the construction phase to linear aggregations of the original indicators and assigning the same role to each MV and/or LV (i.e. a unique system of weights).

QCPM can be considered a quantile approach to PLS path model to construct composite indicators where the indicators could play a different role if referred to units with high or low values. The introduction of Quantile Regression (QR) (Davino et al., 2013; Koenker, 2005) and/or Quantile Correlation (QC) (Li et al., 2015) in the estimation phases of a PLSPM allows to highlight how and if the relationships among observed and unobserved variables change according to the explored quantile of interest.

The present paper shows how QCPM can be considered a proper approach to the analysis of satisfaction data where leverages to improve satisfaction can be different according to the degree of satisfaction. It is a matter of fact that QR is able to distinguish regressor effects on the different parts of the dependent variable distribution, to handle heteroskedastic relationships and highly skewed dependent variables. Moreover a quantile approach is more advisable when data are collected through interval or ordinal scales.

QCPM is proposed to analyse the American Customer Satisfaction Index (ACSI) (ACSI, 2000; Fornell et al., 1996) which represents a well known satisfaction Index. It is a matter of fact that National Customer Satisfaction Indexes represent widespread examples of CS evaluations and they are more and more popular as tools to measure country and company performance. They can be considered as economic indicators measuring CS in several industrial sectors and they can support either the customer in the decisional process and the industries as reference benchmarks and the whole society as a basis for political decisions (Jafari Samimi and Mohammadi, 2011). The most famous and earliest National Customer Satisfaction Indexes are the Swedish (Fornell, 1992), the American (Fornell et al., 1996), the Norwegian (Andreassen and Lindestad, 1998) and the European (ECSI, 1998).

The paper is organized as follows. In Section 2 the methodological framework is given by describing PLSPM and QCPM. The empirical results are presented and discussed in Section 3 following the main steps of a statistical analysis: data description and pre-processing, model estimation, validation and assessment.

2. METHODOLOGICAL FRAMEWORK: PLSPM AND QCPM

The methodological framework of the paper is represented by the QCPM (Davino and Esposito Vinzi, 2014, 2016) which introduces Quantile Regression (Davino et al., 2013; Koenker, 2005) and Quantile Correlation (Li et al., 2015) in the estimation phases of a PLS path model (Esposito Vinzi et al., 2010; Tenenhaus, 1998; Wold, 1985). In this section PLSPM and QCPM are jointly explained showing the main differences among the two methods. QR and QC methodological details are postponed to the Appendix.

A PLSPM is made of a *measurement* (or *outer*) model relating each block of MVs to its corresponding LV and a *structural* (or *inner*) model connecting the LVs in accordance with a network of linear relationships. The aim is to study the relationships among each block of MVs and the corresponding LV as well as among the LVs.

The reference data structure is represented by Q blocks of variables ($\mathbf{X}_q, q = 1, \ldots, Q$) named manifest variables (MVs) related to Q corresponding unobserved concepts named latent variables (LVs) ($\xi_q, q = 1, \ldots, Q$).

QCPM performs all the PLSPM estimation phases using a quantile approach. In particular, it introduces, for each quantile θ of interest, a quantile regression or a quantile correlation in the inner estimation, in the outer estimation as well as in the estimation of the path coefficients and loadings so as to provide estimates of these parameters for each quantile of interest θ.

In the *measurement* model, different kinds of relationships among LVs and MVs can be adopted according to the conceptual definition of the considered LV. The main estimation modes are Mode A (also known as outwards-directed measurement or reflective) and Mode B (also known as inwards-directed measurement or formative). In the classical PLSPM, the former estimation is based on simple linear regressions while the latter on multiple linear regressions. In QCPM simple (Mode A) or multiple (Mode B) quantile regressions allow to compute the LV scores for each quantile of interest. An innovative typology of relationship in the measurement part of the model (named Mode Q) is represented by the use of QC to measure the connection between a LV and each of its MVs (Davino and Esposito Vinzi, 2016). Mode Q allows us to handle both outwards-directed and inwards-directed measurement models because of the asymmetric nature of QC. As in PLSPM, the choice between Mode A and Mode B depends on the conceptual relationship hypothesized between each block of MV and the corresponding LV. Anyway, the scientific debate concerning the choice between formative and reflective indicators is still opened (among many see (Dolce et al., in press; McIntosh et al., 2014; Rigdon, 2014; Vittadini et al., 2007)).

The *inner* model exploits the LV scores defined as the linear combination of the outer weights and the MVs belonging to each block. In particular, each LV is estimated through the LVs it is connected to according to one of the following schemes: path weighting scheme, factorial, centroid. The *path weighting scheme* computes the weights according to the role played by a given j^{th} LV ξ_j with respect to the other LVs it is connected to. In PLSPM, it is the only scheme able to exploit the direction of the links between LVs. In the classical PLSPM, the weights among the ξ_j and its successor LVs (LVs explained by ξ_j, $\xi_{j\rightarrow}$) are determined by their correlations while for its predecessor LVs ($\xi_{\rightarrow j}$) the weights are the coefficients of a multiple regression, where ξ_j is the dependent variable and its predecessor LVs are the regressors. Possible alternatives are the *centroid* and the *factorial scheme*. These schemes are based respectively on the sign and the value of the correlations between LVs. Therefore, they disregard the direction of the links between LVs. In QCPM, if the path weighting scheme is chosen, the inner weights linking the j^{th} successor LV to its predecessors are estimated through a quantile regression:

$$Q_\theta\left(\hat{\xi}_j|\Xi_{\rightarrow j}\right) = \Xi_{\rightarrow j}\hat{\beta}\left(\theta\right) \tag{1}$$

where $\Xi_{\rightarrow j}$ is the matrix of the ξ_j predecessor LVs. Instead, the weights among the j^{th} LV and its successor LVs are determined using the QC described in the Appendix. As in the quantile framework even the correlation is a non symmetric measure, also the use of QC distinguishes between predecessors and successors. QC is also proposed as an alternative to the Pearson correlation coefficient if the centroid or the factorial scheme is adopted.

Both in PLSPM and QCPM, the evaluation of the statistical significance of the coefficients can be carried out exploiting the asymptotically normal distribution of the QR and QC estimators as well as the bootstrap approach classically used in PLSPM and QR. Once an estimation of the coefficient standard errors is obtained, the classical t-test used in regression can allow us to evaluate if each coefficient can be considered significantly different from zero.

The assessment of a QCPM (Davino et al., in press) is performed exploiting the main indexes proposed in the PLSPM framework: communality and average communality for the measurement model and multiple linear determination coefficient (R^2), redundancy index and average redundancy index for the structural model. When a QCPM is performed for different quantiles, a set of assessment indexes for each estimated model are provided.

The communality index measures the amount of the variability of a MV explained by its LV. In the PLSPM framework, it is obtained as the square of the correlation between each MV and its LV or the R^2 of the simple regression where each MV is the dependent variable and the corresponding LV is the regressor. In a quantile framework, the $pseudoR^2$ index (Koenker and Machado, 1999) described in Section 5.2 is used as communality index.

The model assessment can also be carried out for the generic q_{th} block of MVs (Com_q) or for the whole measurement part of the model through averages (weighted by the number of MVs in each block) respectively of the communalities related to the block and to all the MVs. The communality for the whole measurement part is denoted by $\overline{Com}$.

With respect to the structural model in QCPM, the $pseudoR^2$ index is proposed just like the coefficient of determination of the endogenous LVs (Chin, 1998) is used in PLSPM. A $pseudoR^2$ index is computed for each structural equation and each of them measures the amount of variability of a given endogenous LV explained by its predecessor LVs. The average of all the $pseudoR^2$ indexes ($\overline{pseudoR^2}(\theta)$) provides a synthesis of the evaluations regarding the structural part of the model.

Another important index is the *redundancy* because it is able to link the prediction performance of the measurement model to the structural one (Amato et al., 2004). In the QCPM framework the redundancy of a generic j_{th} endogenous LV is proposed as:

$$Red_j(\theta) = Com_j(\theta) \times pseudoR^2(\theta)(\hat{\xi}_j; \hat{\Xi}_{\rightarrow} j) \qquad (2)$$

where $\hat{\Xi}_{\rightarrow} j$ is the matrix of the LVs predictive for the j^{th} LV. The only difference with the PLSPM redundancy is the use of the $pseudoR^2$ index in place of the coefficient of determination.

An overall assessment of the quality of the structural part is provided by the average redundancy ($\overline{Red}(\theta)$) obtained as a mean of the redundancies associated to the set of endogenous LVs.

The different options available in a QCPM are summarized below, highlighting in brackets the methodology involved:

- outer scheme: Mode A (simple QR), Mode B (multiple QR), Mode Q (QC);
- inner scheme: path weighting (QR and QC), factorial (QC), centroid (QC sign);
- assessment: communality and redundancy index ($pseudoR^2$).

According to the choice adopted in the various estimation phases, different versions of the QCPM are available.

3. THE AMERICAN CUSTOMER SATISFACTION INDEX MEASUREMENT

3.1 ACSI DESCRIPTION AND PRE-PROCESSING

QCPM is applied to a real dataset concerning the ACSI (ACSI, 2000; Anderson and Fornell, 2000)[2]. This index was established in 1994 and it measures the satisfaction of U.S. household consumers with respect to the quality of products and services offered by firms belonging to different sectors. Our application refers to the *apparel* sector including 777 observations. The customer satisfaction is driven by three factors (customer expectations, perceived value and perceived quality) and has loyalty as outcome. The complaints LV has been excluded because the number of complaints was very small (1% of the sample). The five LVs are interrelated according to the structural model in Figure 1.

[2] http://www.theacsi.org/

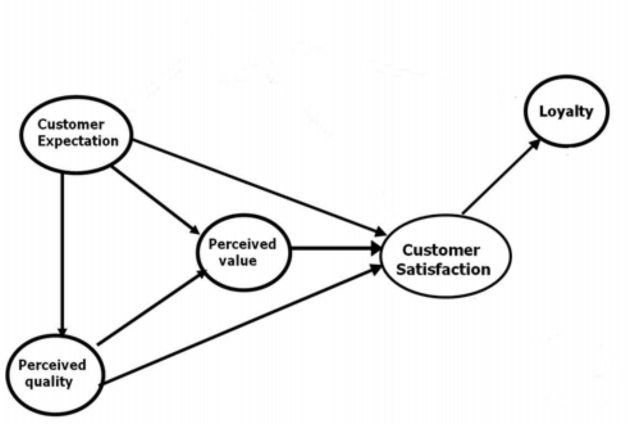

Figure 1: Structural model describing driving factors and outcomes of customer satisfaction

Each LV is measured through a set of indicators measured on a scale 1–10. (Table 1); labels that will be used in result graphs and tables are represented in brackets and in the third column.

Table 1: LVs and MVs of the ACSI dataset

LV	MV	Label
Customer Expectations (Expectation)	Expectations about overall quality Expectations about customization Expectation about reliability	OVERALLX CUSTOMX WRONGX
Perceived Quality (Quality)	Meeting personal requirements Things went wrong	CUSTOMQ WRONGQ
Perceived Value (Value)	Price given Quality Quality given Price	PQ QP
Customer Satisfaction (Satisfaction)	Customer Satisfaction Overall Quality Confirmation to Expectations Close to ideal product/service	SATIS OVERALLQ CONFIRM IDEAL
Customer Loyalty (Loyalty)	Repurchase Intention	REPUR

A reflective model is adopted in the measurement part assuming that each block of MVs measures a unique underlying concept. This choice is quite common in the assessment of CS (ACSI, 2000; ECSI, 1998; Hagerty and Land, 2007; Zanella, 1999) and of unobservable psychological constructs (McIntosh et al., 2014).

A descriptive analysis is crucial because it allows to select the best set of MVs and to properly transform them to be used in a multivariate model. At this regard, in addition to classical univariate and bivariate statistics, in case of reflective blocks of MVs it is necessary to check for unidimensionality in the meaning of factor analysis. For this purpose the three main tools in PLSPM are: principal component analysis of each block of MVs, Cronbach's α and Dillon-Goldstein's ρ. A block is essentially unidimensional if the first eigenvalue of the correlation matrix of the block MVs is larger than 1 and the second one smaller than 1, or at least very far from the first one. Cronbach's α can be used to quantify consistency of a block of positively correlated variables. A block is considered as internally consistent when the Cronbach's α and/or the Dillon-Goldstein's ρ are larger than 0.7.

The statistics for checking the unidimensionality of each block are shown in Table 2 and they lead to an acceptation of the unidimensionality of all blocks. Statistics for block loyalty are not shown as this block consists of a single MV.

Table 2: Check for block unidimensionality

LV	MV number	Cronbach's α	Dillon's ρ	1^{st} eigenvalue	2^{nd} eigenvalue
Expectation	3	0.699	0.834	1.883	0.716
Quality	2	0.667	0.857	1.500	0.500
Value	2	0.834	0.923	1.716	0.284
Satisfaction	4	0.868	0.910	2.867	0.469

After the data description phase, a pre-processing of the variables can be advisable for several reasons; for example, quantitative MVs can have different unit measurements or qualitative MVs are recommended to be transformed into dummy variables. In a PLSPM framework, the standardisation of the variables is often recommended because it facilitates the algorithm convergence and provides standardised LV scores easier to be interpreted. A further exploration suggested in case of a QCPM is the analysis of the MV variability. Especially in case of discrete MVs representing scores varying in a small range, it is typical a concentration of responses on the upper part of the scale. In such cases, it results that from a given quantile forward the considered variable is characterised by an absence of variability. In a QCPM such a quantile represents the highest quantile interesting to be explored. This information is not evident exploring some of the classical univariate graphs and statistics while it is highlighted by the quantile values. Figure 2 and Table 3 show respectively the distributions and the main univariate statistics (standard deviation, skewness coefficient, mean and five quantiles) related to the ACSI MVs. It is worth noticing how for all the MVs a big part of responses are concentrated on the highest score of the scale thus providing a reduced variability, asymmetric distributions and several quantiles all equal to 10.

Table 3: MV univariate statistics

MV	sd	skewness	mean	θ=0.1	θ=0.25	θ=0.5	θ=0.75	θ=0.9
OVERALLX	1.53	-1.34	8.37	6	8	9	10	10
CUSTOMX	1.59	-1.35	8.47	6	8	9	10	10
WRONGX	2.27	-1.14	7.91	5	7	8	10	10
CUSTOMQ	1.69	-1.64	8.37	6	8	9	10	10
WRONGQ	2.23	-1.53	8.26	5	8	9	10	10
PQ	1.86	-1.08	7.77	5	7	8	9	10
QP	1.75	-1.27	8.11	6	7	8	10	10
SATIS	1.69	-1.61	8.37	6	8	9	10	10
OVERALLQ	1.56	-1.55	8.36	7	8	9	9	10
CONFIRM	1.88	-0.97	7.41	5	6	8	9	10
IDEAL	2.00	-1.13	7.54	5	7	8	9	10
REPUR	2.30	-1.26	7.84	5	7	8	10	10

In Figure 3, for each MV, the distribution of the percentage of customers expressing an evaluation equal to 10 is shown. From this information it is possible to identify for each MV the maximum quantile interesting to explore as complement to 1 of the relative highest frequency associated to the maximum value. For example, it is not interesting to explore the variable WRONGQ from the 0.59 quantile forward because all the quantiles will be equal to 10. Even if the maximum quantile is different for each MV, the analysis cannot be performed beyond the minimum threshold quantile which corresponds to 0.59. The requirement to confine the analysis at a lower quantile cannot be considered a limit of the QCPM because the method is finalized to the exploration of the different parts of a dependent variable distribution when they are characterised by different and not constant effects of the regressors.

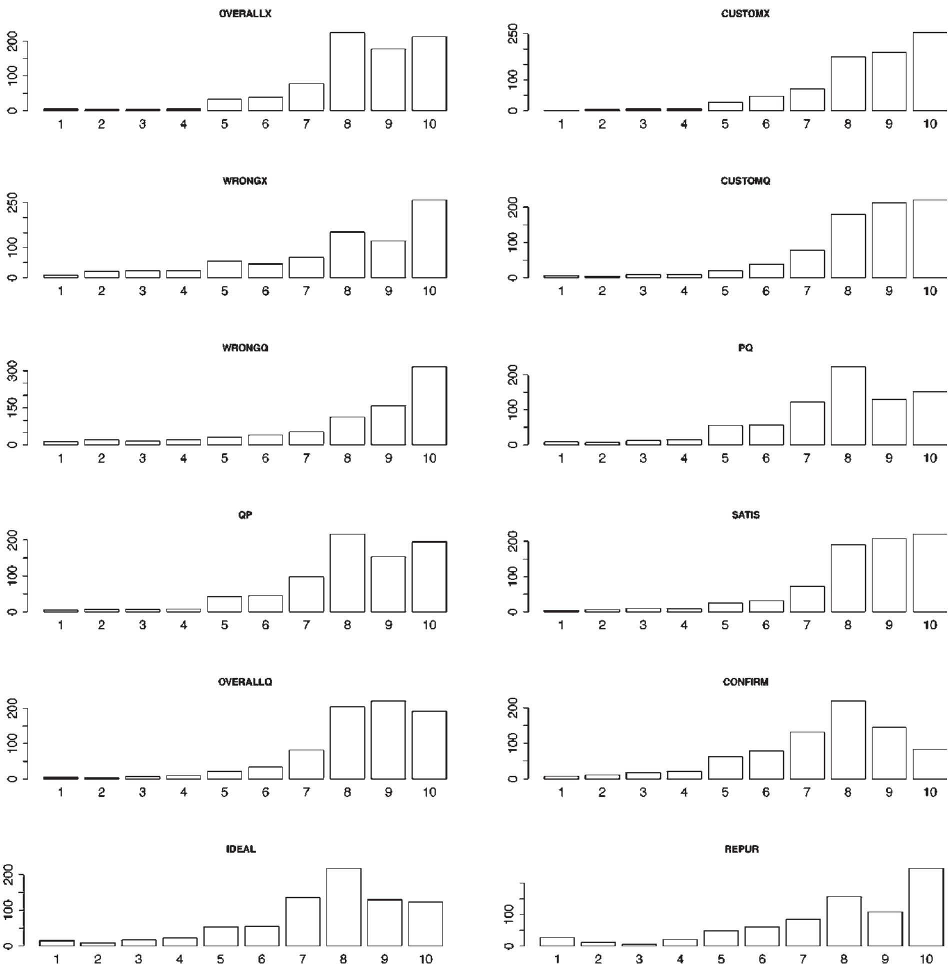

Figure 2: Bar charts of the MVs

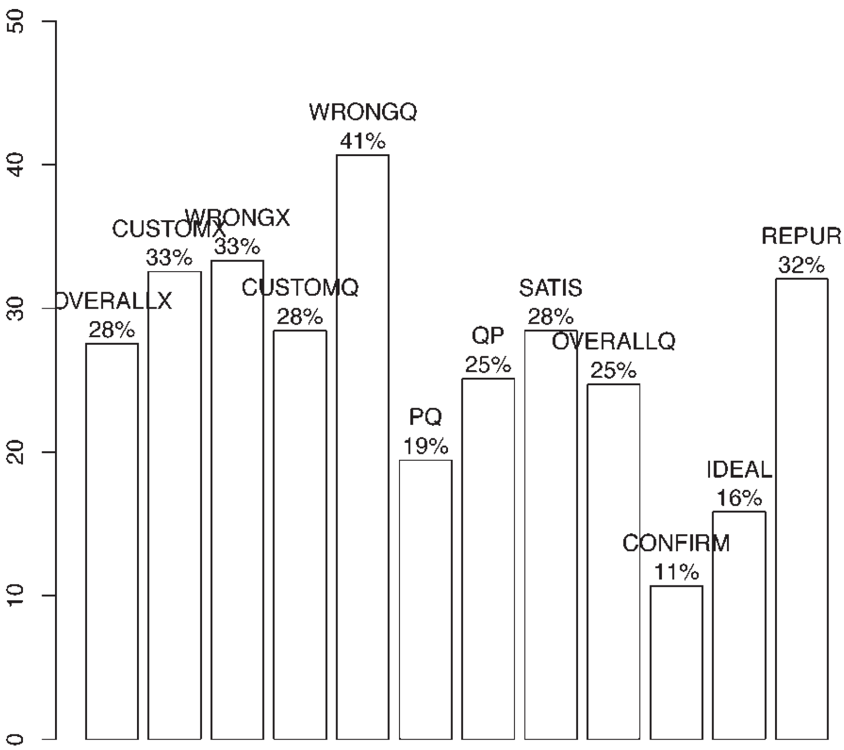

Figure 3: Percentage of customers expressing an evaluation equal to 10 for each MV

3.2 ACSI ESTIMATION AND VALIDATION

The ACSI application has been realised applying a QCPM to standardised MVs, with a centroid scheme in the inner estimation and an outwards-directed relationship in the outer estimation. In both the estimation phases quantile correlation has been used.

A selected grid of quantiles of interest has been chosen till the minimum threshold quantile: θ =[0.1, 0.25, 0.5, 0.59]. Table 4 shows the outer weights obtained from the ACSI dataset choosing Mode Q in the outwards-directed measurement model; significant coefficients at α = 0.10 are in bold. It is worth noticing differences among the MV average effects represented by the PLSPM coefficients and the MV impacts at different quantiles.

The aim of the analysis is to show how QCPM can complement the informa-

Table 4: QCPM and PLSPM outer weights

MV	PLSPM	θ=0.1	θ=0.25	θ=0.5	θ=0.59
OVERALLX	**0.398**	**0.382**	**0.375**	**0.320**	**0.363**
CUSTOMX	**0.505**	**0.465**	**0.479**	**0.442**	**0.508**
WRONGX	**0.347**	**0.415**	**0.406**	**0.504**	**0.383**
CUSTOMQ	**0.678**	**0.655**	**0.640**	**0.583**	**0.590**
WRONGQ	**0.469**	**0.495**	**0.512**	**0.571**	0.564
PQ	**0.470**	**0.442**	**0.490**	**0.435**	**0.565**
QP	**0.607**	**0.634**	**0.588**	**0.641**	**0.514**
SATIS	**0.325**	**0.278**	**0.323**	**0.322**	**0.322**
OVERALLQ	**0.310**	**0.364**	**0.300**	**0.271**	**0.269**
CONFIRM	**0.277**	**0.273**	**0.264**	**0.288**	**0.289**
IDEAL	**0.266**	**0.264**	**0.292**	**0.299**	**0.300**

tion provided by PLSPM. For example, let us consider the OVERALLQ (overall quality) MV belonging to the block related to the Customer satisfaction LV. The coefficient obtained performing a PLSPM (0.310) suggests that for a unitary increase of the overall quality, the average customer satisfaction increases of 0.310. An improvement on the evaluation of the overall quality produces a higher effect (0.364) on the less satisfied customers belonging to the first 10% of the distribution. From an operational point of view, that means that if a firm invests on this aspect of the quality of products, it will benefit of a major effect on the 10^{th} conditioned quantile of the customer satisfaction.

With respect to the WRONGQ (things went wrong) MV, the variable with the biggest concentration of responses on the highest part of the distribution, its effect on the perceived quality is higher performing a QCPM with respect to the PLSPM average result.

In PLSPM, the analysis of the outer weights of the MVs is very useful to identify the strategic levers to improve customer satisfaction. At this regard, it is interesting to compare the impact of each MV with respect to the MV average. Critical circumstances occur when customers are dissatisfied about an aspect (a MV) resulting very important according to the role it plays in the measurement model. In a PLSPM framework such an evaluation can be supported by a graphical representation where the scatter plot of the MVs is obtained with respect to the normalised outer weights and the MV averages (Figure 4). The average of the normalised outer weights (*normw_ave*) and the global MV average (*global_ave*) can be considered reference values to suggest satisfaction improvements. In Figure 4 a vertical and horizontal line has been superimposed respectively in position *global_ave* and *normw_ave* to the scatter plot of the MVs according to the PLSPM normalised outer weights and to the MV averages. The first reflection to be done is that all the MVs received good evaluations so that even MV averages below the *global_ave* cannot be considered particularly negative. The average lines separate the plane in four quadrants, representing different frameworks for the CS evaluation and improvement. The first quadrant (I) represents solid CS components, key factors whose satisfaction can be considered as crucial with respect to their importance (average values higher than *global_ave*) and strengthened with respect to their evaluation (MV averages higher than the respective *normw_ave*). The second quadrant (II) represents issues to be improved as they have received average evaluations lower than the global average but customers have assigned them high weights. The third quadrant (III) is not very interesting because it contains not relevant indicators even if with average values below the global average. The fourth quadrant (IV) still considers not significant aspects (low weights) but stable because of the high average evaluations.

In case of the QCPM, four scatter plots (one for each considered quantile) are obtained (Figure 5). Most of the MVs stay in the same quadrants as in Figure 4 but PQ and WRONGX. From PLSPM results such indicators could not be considered critical aspects (actually PQ was in a border line position). Moving from lower to upper satisfaction quantiles, the role of PQ becomes critical. In terms of normalised weights the differences among the quantiles appear negligible but in terms of absolute values (Table 4) they are more substantial. From a practical point of view, that means that to improve satisfaction with respect to price given quality it is necessary to act on the most satisfied customers.

Differences in the coefficient sizes can be also appreciated using a graphical representation. In Figure 6 the bar charts of the normalised outer weights for the four selected quantiles and for the classical PLSPM are shown. Figure 6 provides a different focus on the results because they are analysed separately for each LV and with respect to MV trends across the quantiles. For example, moving from lower to upper quantiles the coefficient trend is decreasing for CUSTOMQ and increasing for WRONGQ.

Table 5 shows the path coefficients obtained using the centroid scheme in a PLSPM and in QCPM for a selected grid of quantiles of interest; in bold significant coefficients at $\alpha = 0.1$. QR provides, for each quantile of interest, a couple

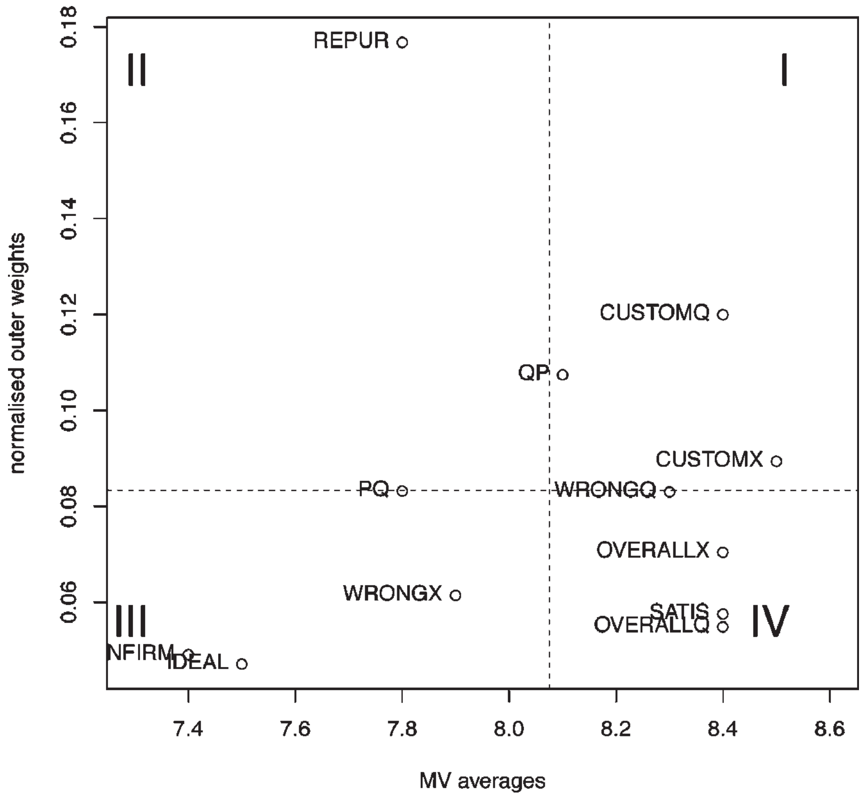

Figure 4: PLSPM normalised outer weights with respect to MV averages

of parameters, one corresponding to the quantile regression coefficient (the slope) and one to the intercept. From the interpretative point of view the former is the most interesting and it should be compared with the corresponding PLSPM coefficient while the latter just represents a location parameter.

That means that a structural equation showing similar slopes and different intercepts at different quantiles represents a pure location shift model. In such a case, the quantile regression estimates are expected to be quite similar to the PLSPM coefficients. On the other hand, it is more interesting to make use of a QCPM when it provides coefficients different in size and sign across quantile thus providing location, scale and shape shift information on the dependent variable.

A graphical representation of the coefficients is more effective in highlighting differences among PLSPM and QCPM results and among QCPM coefficients at different quantiles. In Figure 7 the horizontal axis refers to the estimated quantile,

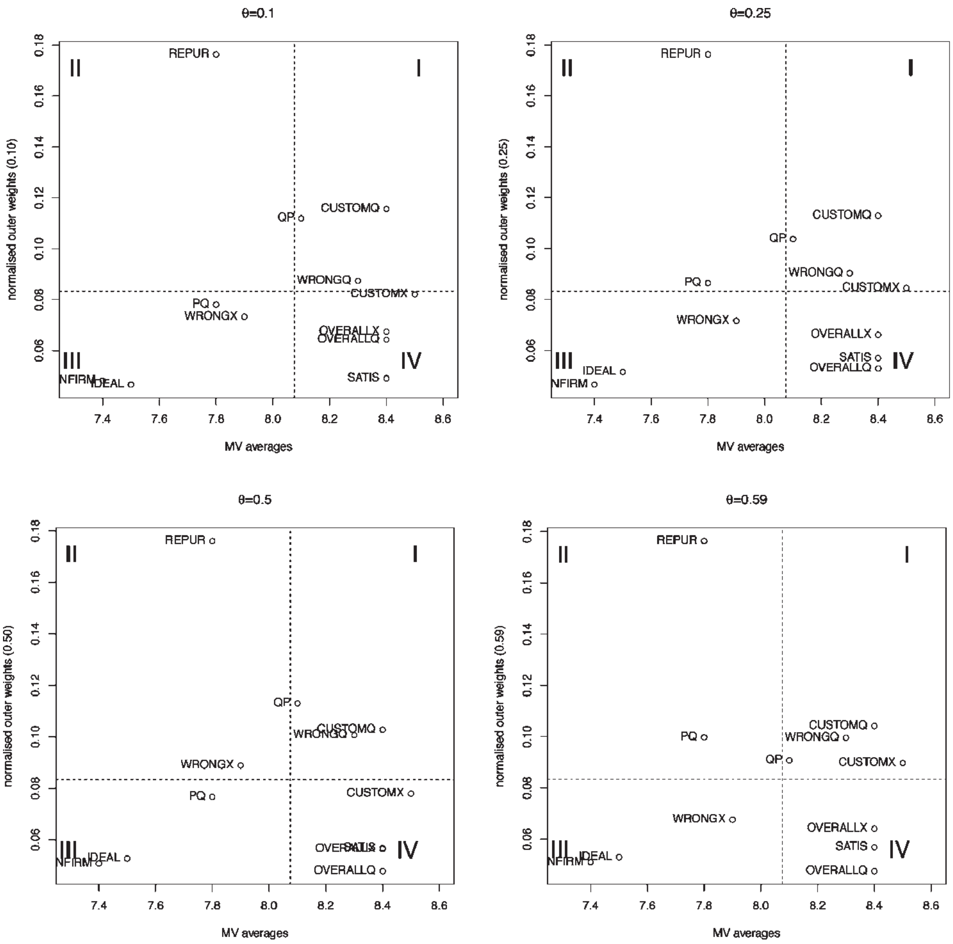

Figure 5: QCPM normalised outer weights with respect to MV averages

the vertical axis to the corresponding coefficient and each segment represents the QCPM coefficients of each LV impacting on the considered LV. Circles refer to the path coefficients obtained from a classical PLSPM, full circles and stars represent significant coefficients at $\alpha = 0.10\%$ respectively from PLSPM and QCPM. For easiness of interpretation, PLSPM results are vertically alligned to the median results. It is worth noting that path coefficients differentiate in the extreme parts of the distribution, meaning that the impact of a given LV is different on very low or very high satisfied customers. For example, considering the *expectation* LV, its effect on the *quality* LV decreases moving from the first 10% of the distribution to the last considered quantile.

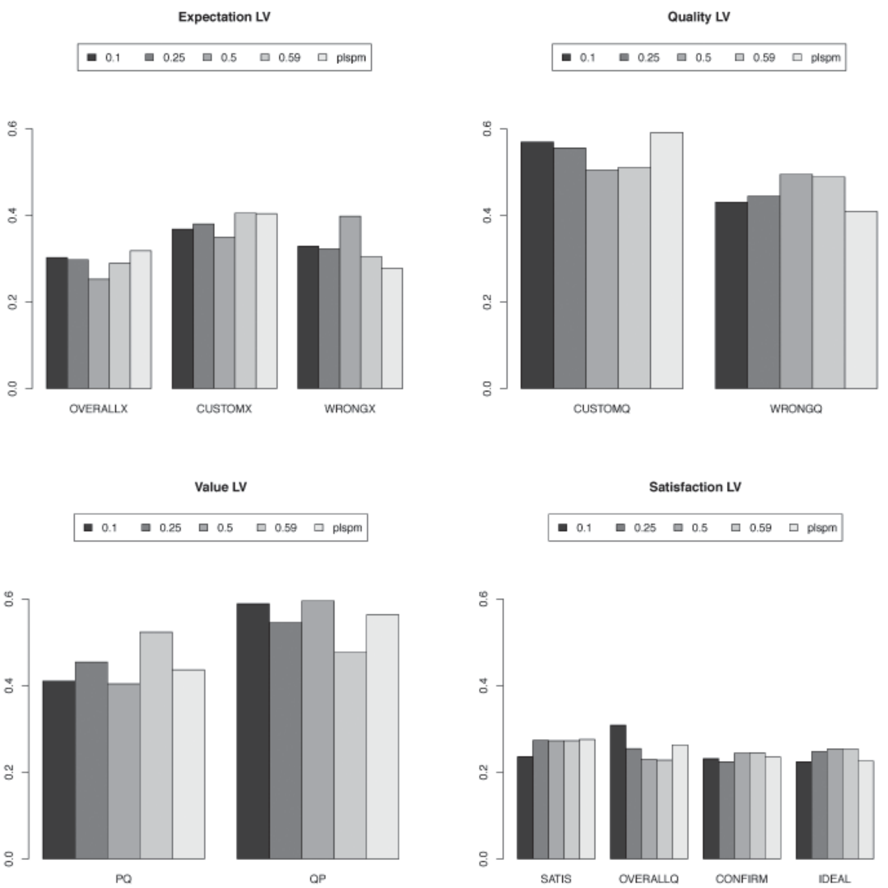

Figure 6: QCPM and PLSPM normalised outer weights

Table 5: Path coefficients from a classical PSLPM and from a QCPM for a selected set of quantiles (θ = [0.1,0.25,0.5,0.59])

LV	MV	PLSPM	θ=0.1	θ=0.25	θ=0.50	θ=0.59
quality	Intercept	0.000	**-0.891**	**-0.363**	**0.105**	**0.240**
	Expectation	**0.611**	**0.788**	**0.778**	**0.733**	**0.625**
Value	Intercept	0.000	**-0.905**	**-0.405**	0.045	**0.195**
	Expectation	**0.104**	0.066	0.057	**0.125**	**0.136**
	Quality	**0.583**	**0.713**	**0.694**	**0.543**	**0.525**
Satisfaction	Intercept	0.000	**-0.619**	**-0.296**	0.021	**0.128**
	Expectation	**0.140**	**0.143**	**0.103**	**0.125**	**0.164**
	Quality	**0.448**	**0.591**	**0.527**	**0.426**	**0.400**
	vValue	**0.414**	**0.384**	**0.405**	**0.435**	**0.410**
Loyalty	Intercept	0.000	**-0.853**	**-0.333**	**0.086**	**0.208**
	Satisfaction	**0.688**	**0.848**	**0.827**	**0.728**	**0.693**

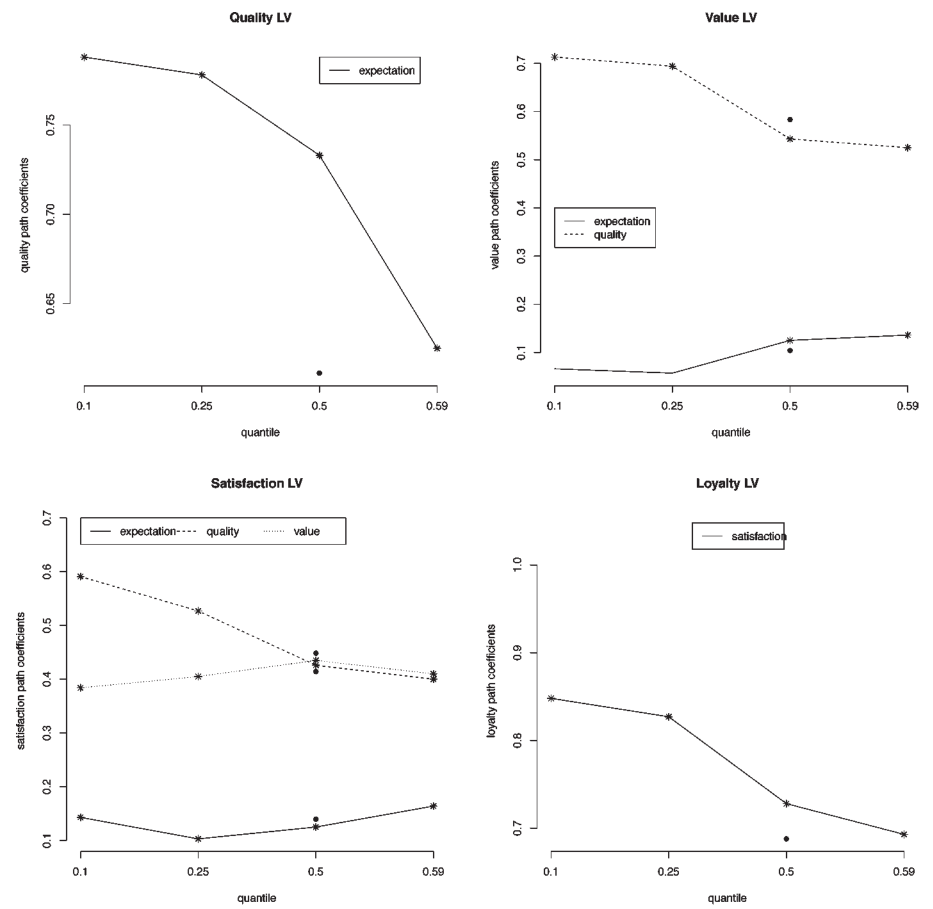

Figure 7: QCPM and PLSPM path coefficients for a set of selected quantiles

3.3 ACSI ASSESSMENT

The first issue to be faced in a model assessment phase is the evaluation of correlations among MVs and LVs (loadings). The results are expected to show higher loadings relating each block of MV to the corresponding LV with respect to the link with all the other LVs (cross loadings). The aim is to measure if the concept underlying each LV differs from the other unobserved constructs.

In Table 6 PLSPM loadings and crossloadings show that each MV is more

Table 6: PLSPM loadings and crossloadings greater than 0.5

MV	Expectation	Quality	Value	Satisfaction	Loyalty
OVERALLX	**0.808**				
CUSTOMX	**0.879**	0.542		0.591	
WRONGX	**0.675**			0	
CUSTOMQ	0.578	**0.914**	0.653	0.822	0.607
WRONGQ		**0.809**		0.519	
PQ		0.507	**0.905**	0.637	0.503
QP		0.672	**0.944**	0.772	0.588
SATIS	0.524	0.755	0.754	**0.903**	0.630
OVERALLQ	0.623	0.740	0.613	**0.860**	0.563
CONFIRM		0.644	0.636	**0.827**	0.552
IDEAL		0.557	0.590	**0.792**	0.584
REPUR		0.588	0.594	0.688	**1.000**

correlated to its own latent variable than to the other LVs. To make this table easier to read, correlations below 0.5 are not shown.

In Table 7 PLSPM and QCPM loadings are shown; in italics the highest loading provided by QCPM for each MV and in bold QCPM loadings higher than PLSPM. QCPM loadings are computed as quantile correlations where each MV plays the role of dependent variable in the block it belongs to. The results are satisfactory for most of the LVs (for sake of space cross-loadings are not shown but they are in all cases lower than the loadings). It is interesting the variability of the loadings across the quantiles. For example, the correlation of OVERALLQ to the *Expectation* LV is higher in the lower part of the distribution (θ=0.1) and even greater than the PLSPM loading. The worst loading provided by PLSPM is related to WRONGX but it improves if the lowest part of the distribution is separately analysed. Even if some results provided by QCPM with θ=0.5 and θ=0.59 are not satisfactory, (showing quantile correlation coefficients lower than 0.5) they represent in any case values greater than the crossloadings (with the exception of REPUR).

Table 8 shows the indexes for the measurement model assessment provided by PLSPM and QCPM (in italics the highest values across the quantiles with respect to a given MV and in bold QCPM communality values higher than PLSPM). Even if the amount of variability explained by each LV is low in some cases, it is

Table 7: PSLPM and QCPM loadings for a selected set of quantiles (θ = [0.1,0.25,0.5,0.59])

MV	PLSPM	θ=0.1	θ=0.25	θ=0.50	θ=0.59
OVERALLX	0.808	0.609	*0.714*	0.453	0.484
CUSTOMX	0.879	0.681	*0.811*	0.525	0.561
WRONGX	0.675	***0.711***	0.708	0.647	0.479
CUSTOMQ	0.914	0.740	*0.787*	0.476	0.485
WRONGQ	0.809	0.715	*0.792*	0.585	0.593
PQ	0.905	0.729	*0.804*	0.618	0.655
QP	0.944	*0.858*	0.774	0.704	0.491
SATIS	0.903	0.747	*0.769*	0.465	0.473
OVERALLQ	0.860	***0.970***	0.741	0.387	0.393
CONFIRM	0.827	*0.782*	0.683	0.471	0.479
IDEAL	0.792	*0.756*	0.754	0.494	0.503
REPUR	1.000	0.431	*0.438*	0.331	0.249

interesting the variability across the quantiles and the presence of some quantiles where the measurement model assessment is better. For example, the communality representing the amount of variability of the IDEAL MV explained by the *satisfaction* LV remains almost constant across the quantiles and lower than 50%. In case of other MVs such as CUSTOMQ and PQ, there are interesting differences among the quantiles. In the former case the *quality* LV is able to explain more than 74% of the CUSTOMQ variability in the first 10% of the distribution and just a little more than 50% in case of the most satisfied customers. The opposite happens for the PQ case.

The assessment of the communality related to the four blocks provides satisfactory results particularly for the *quality* and the *value* LVs with respect to the other QCPM results. In the first case it is interesting the communality value associated to QCPM with $\theta = 0.1$. Turning to a quantile approach to PLSPM proves to be penalising from the assessment of the whole measurement model point of view (*com* values).

Table 9 shows the indexes for the structural model assessment while Table 10 shows the redundancy indexes provided by PLSPM and QCPM (in italics the highest values across the quantiles with respect to a given MV). Notwithstanding the interesting variability of the indexes across the quantiles, the overall assess-

Table 8: Communality indexes for the measurement model assessment

LV	MV	PLSPM	θ=0.1	θ=0.25	θ=0.5	θ=0.59
Expectation	OVERALLX	0.653	*0.483*	0.449	0.392	0.407
	CUSTOMX	0.772	*0.618*	0.591	0.476	0.499
	WRONGX	0.456	0.391	0.405	*0.441*	0.347
	$Com_{Expectation}$	0.627	0.559	0.564	0.566	*0.597*
Quality	CUSTOMQ	0.835	*0.743*	0.669	0.587	0.543
	WRONGQ	0.655	0.585	*0.593*	0.571	0.534
	$Com_{Quality}$	0.745	0.635	*0.672*	0.670	0.664
Value	PQ	0.820	0.577	0.632	0.648	*0. 731*
	QP	0.892	*0.782*	0.776	0.766	0.656
	Com_{Value}	0.856	*0.673*	0.664	0.618	0.588
Satisfaction	SATIS	0.815	*0.661*	0.623	0.554	0.513
	OVERALLQ	0.740	*0.635*	0.544	0.457	0.408
	CONFIRM	0.684	0.436	*0.465*	0.460	0.448
	IDEAL	0.628	0.436	*0.467*	0.435	0.438
	$Com_{Satisfaction}$	0.717	*0.634*	0.603	0.601	0.577
$\overline{Com}$		0.723	*0.621*	0.616	0.607	0.600

Table 9: R^2 and $pseudoR^2$

LV	PLSPM	θ=0.1	θ=0.25	θ=0.5	θ=0.59
Quality	0.373	0.263	*0.292*	0.238	0.211
Value	0.425	*0.318*	0.267	0.219	0.199
Satisfaction	0.762	*0.604*	0.546	0.468	0.446
Loyalty	0.473	0.330	*0.348*	0.315	0.298

ment of the structural part shows rather low values of the R^2, $pseudoR^2$ and consequently redundancy values. This is probably due to the presence of endogenous LVs explained by few (or even one) LVs (Chin, 1998). Moreover, in case of the QCPM, it is well known that the typical determination index is not a satisfactory assessment index (Koenker and Machado, 1999).

4. CONCLUDING REMARKS

QCPM, which jointly exploits PLSPM and QR potentialities, is proposed in the CS framework. In particular, the American Customer Satisfaction measurement is performed showing at the same time PLSPM and QCPM results. It is worth of noticing that the interpretation of the results is carried out taking into account that QCPM can be considered a method complementary to PLSPM. The analysis of the outer weights revealed that the impact of some MVs on the corresponding LV varies in the different parts of the dependent variable distribution. In such cases actions based on the average effect provided by PLSPM coefficients can be considered a limiting approach. The obtained path coefficients are even more differentiated across the quantiles, especially in the extreme parts of the dependent variable distribution which are the most discriminating in a CS framework.

Table 10: Redundancy indexes

LV	MV	PLSPM	θ=0.1	θ=0.25	θ=0.5	θ=0.59
Quality	CUSTOMQ	0.312	*0.196*	0.195	0.140	0.114
	WRONGQ	0.244	0.154	*0.173*	0.136	0.112
	$Red_{Quality}$	0.278	0.147	*0.165*	0.135	0.126
Value	PQ	348	*0.183*	0.169	0.142	0.145
	QP	0.379	*0.248*	0.207	0.168	0.130
	Red_{Value}	0.364	*0.202*	0.180	0.147	0.132
Satisfaction	SATIS	0.621	*0.400*	0.340	0.259	0.229
	OVERALLQ	0.564	*0.384*	0.297	0.214	0.182
	CONFIRM	0.521	*0.263*	0.254	0.215	0.200
	IDEAL	0.478	*0.264*	0.255	0.204	0.195
	$Red_{Satisfaction}$	0.546	*0.407*	0.363	0.289	0.262
Loyalty	REPUR	0.473	0.330	*0.348*	0.315	0.298
	$Red_{Loyalty}$	0.473	*0.209*	0.210	0.189	0.172
mean		0.415	*0.241*	0.230	0.190	0.173

5. APPENDIX

5.1 QUANTILE REGRESSION

An extension of OLS to the estimation of a set of conditional quantile functions is represented by QR (Koenker and Basset, 1978, 1982a,b). For a given quantile θ, a QR model can be formulated as follows:

$$Q_\theta\left(\hat{\mathbf{y}}|\mathbf{X}\right) = \mathbf{X}\hat{\beta}\left(\theta\right) \tag{3}$$

where $\mathbf{y}$ is the response variable observed on n individuals, $\mathbf{X} = [\mathbf{1}, \mathbf{X}_p]$ is a matrix with p regressors and a vector of ones for the intercept estimation, $0 < \theta < 1$ and $Q_\theta(.|.)$ denotes the conditional quantile function for the θ^{th} quantile.

Although different functional forms can be used, the paper will refer to linear regression models. In a QR, no probabilistic assumptions are required for the errors. The parameter estimates in QR linear models have the same interpretation as those of any other linear model. As a consequence, the estimated values of the response variable conditioned to given values of the regressors, reconstruct the conditioned quantile of the dependent variable.

QR estimators are asymptotically normally distributed with different forms of the covariance matrix depending on the error model assumptions. Resampling methods can represent a valid alternative to the asymptotic inference (among many authors, see: Kocherginsky et al., 2005) because they allow the estimation of parameter standard errors without requiring any assumption in relation to the error distribution.

The assessment of goodness of fit for the QR model exploits the general idea leading to the typical R^2 goodness of fit index in classical regression analysis. The most common goodness of fit index in the QR framework, is called $pseudoR^2$ (Koenker and Machado, 1999). For each considered quantile θ, it compares an absolute sum of weighted residuals using the selected model (corresponding to the residual sum of squares in classical regression) with an absolute sum of weighted residuals (corresponding to the total sum of squares of the dependent variable in classical regression) using a model with only the intercept. The $pseudoR^2_\theta$ ranges between 0 and 1 and it can be considered a measure of the goodness of fit of a model estimated at a give quantile. In practice, for each considered quantile, the corresponding $pseudoR^2_\theta$ is provided. Moreover, it is well known in QR literature (Koenker and Machado, 1999) that the $pseudoR^2$ is a simplistic adaptation of the R^2 and thus it always produces pessimistic results with respect to those provided by R^2 in OLS regression.

5.2. QUANTILE CORRELATION

The quantile correlation index, introduced by Li et al. (2014) as a correlation measure between two random variables Y and X for a given quantile $\theta \in (0,1)$, is given by:

$$qcor_{\theta}\{Y,X\} = \frac{qcov_{\theta}\{Y,X\}}{\sqrt{(\theta-\theta^2)\,var(X)}}. \qquad (4)$$

where $qcov_{\theta}\{Y,X\} = cov\{I(Y-Q_{\theta}(Y)>0),X\}$, $Q_{\theta}(Y)$ is the θ^{th} unconditional quantile and $I(\cdot)$ is the indicator function.

QC has the same properties as a correlation coefficient but it is not symmetric. For this reason it is necessary to identify the role played by the involved variables; in Equation 4 the Y variable is considered as the dependent variable.

To evaluate the significance of QC, as the estimation of the variance of the QC estimator is rather complex, a bootstrap approach is proposed (Davino and Esposito Vinzi, 2016) for this purpose.

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