QUANTILE REGRESSION FOR THE EVALUATION OF STUDENT SATISFACTION[1]

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Abstract

This paper aims to analyse the internal effectiveness of a University educational process through quantile regression. Such approach allows to take into account the effect the main features of a course play on student satisfaction. As a matter of fact quantile regression allows to focus on the effects that the explanatory variables have on the entire conditional distribution of the dependent variable and it is then able to catch the different effect of course features for unsatisfied and very satisfied students. Moreover, the quantile regression estimates are used to detect typologies either exploiting a stratification variable or using similarities in the dependence model.

Keywords: quantile regression, student satisfaction, group effects.

1. INTRODUCTION

Nowadays, the evaluation of high educational institutions plays a crucial role both for directing the improvement policies and for the funding allocation. Effectiveness is one aspect to take into account in such evaluation. It concerns the com-

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parison between the expected and the obtained results deriving from the educational processes (Aitkin & Longford 1986), (Lockheed & Hanushek 1994), (Gori & Montagni 1997), (Eide & Showalter 1998), (Gori & Vittadini 1999), (Davino & Vistocco 2007).

The aim of this paper is to investigate on the internal effectiveness of high educational Institutions from the student perspective. Since student satisfaction (SS) is a complex concept and it is not directly measurable, the building blocks for obtaining information on it are the satisfaction levels of the main features of a course. In fact, different are the factors: course design, teacher ability, infrastructures, influencing the SS. For each factor, it is possible to find a set of indicators to evaluate how much each of them affects SS. The analysis proposed in this paper is conducted through quantile regression (Koenker & Basset 1978) (Hao & Naiman 2007). It is a regression technique which allows to focus on the effects that the explanatory variables have on the entire conditional distribution of the dependent variable, namely it takes into account that this effect can be different for students with different levels of satisfaction.

Furthermore, the quantile regression potentiality to explore the entire conditional distribution of a response variable is exploited to identify a typology, namely groups of students characterized by similar dependence structures. The detection of a typology can be also carried out using a classification approach whereas an a priori group variable is available. The proposed procedure is used in this paper in the context of the evaluation of student satisfaction but many are the applicative contexts where it could be fruitful.

The paper is organized as follows: the description of the data is provided in Section 2 while quantile regression methodological details and the corresponding results are explored in Section 3. The proposed approach for the detection of a typology is described in Section 4 together with the main results. The final part of the section includes the extension of the analysis whereas a priori defined groups are available. Some concluding remarks and future work directions are described in the final section.

2. THE DATASET

As stated before, the aim of the empirical analysis is to evaluate how much the different features of a course affect student satisfaction taking into account that this effect can be different for unsatisfied and very satisfied students. The evaluation is based on the analysis of data coming from a survey which is undertaken each year at University of Macerata to monitor student satisfaction with respect to the courses they attend. The analysis is based on the data collected about all the courses of the academic year 2006/2007. Therefore the data can be considered as the population of students that attend courses in the considered academic year (13125 students). Even if an inferential phase could not be strictly required, the paper presents statistical significance results too, as the population of students in each academic year can be referred to a theoretical model of sub-population (Cochran 1977). In such a framework, the significance levels of coefficients should be considered. Notwithstanding, it is worth of notice that the dimension of the considered sub-population (more than 13000 units) suggests caution in interpreting inferential results, for the well known problems affecting classical test procedures in case of such large samples (Glymour et al. 1996).

The main hypothesis behind the survey design is that many are the components of a successful course and each of them have to be considered to evaluate the overall satisfaction. The relevant features of a course have been organized in the following sections of the questionnaire:

Section Course Design: conditions to take exams (C1), schedule of the course (C2), availability of the teacher (C3), co-ordination with other courses (C4);

Section Teaching and Study: preliminary knowledge required (D1), interest attraction capability of the teacher (D2), clearness of the teacher (D3), heavy study load (D4), suitable materials for studying (D5), explained topics with respect to time (D7), interaction with the teacher during the lessons (D10);

Section Infrastructures: comfort of classrooms (E1).

The dependent variable is the overall student satisfaction.

All the variables have been observed on a four-level ordinal scale (definitely unsatisfied, unsatisfied, satisfied, definitely satisfied). Such kind of variables are usually coded in a four-level cardinal scale: it is indeed quite common to approach these variables through the substitution of numbers to the qualitative modalities under the assumption of the existence of a not directly measurable continuous variable expressing the score. The variables obtained under such assumption can then be treated as numerical ones.

The quantification approach followed in this paper has been proposed by Chiandotto and Gola (Chiandotto & Gola 1999) in the specific context of student satisfaction evaluation. In particular, they proposed to assign the following scores to each category: 2, 5, 7, 10. It is a matter of fact that the quantification problem can be faced through many alternatives: for a survey of the literature on the topic see (Zanella 2001) and (Rizzi 2008). Quantification strategies can be classified in direct and indirect quantification methods (Kline 2000). Direct methods force the distance between pairs of categories to be equal but they can be useful when no information is available on the real distribution of the corresponding scores. On the other hand, the indirect quantification methods allow to assign no equidistant values to the categories but they require distributional assumptions on the continuous latent score.

The quantification strategy used in this paper can be considered as a compromise solution as no equidistant values are assigned to the categories but no assumption are required on the continuous latent score. Notwithstanding the arbitrariness of the choice followed in the paper, the transformation is quite agreed from the Italian scientific community and accepted by the National Committee for University System Evaluation (CNVSU) (Chiandotto & Gola 1999).

Before describing the main results of the quantile regression, it is interesting to have a glance at the coefficients estimated by a classical least squares (LS) regression (Table 1, in bold significant coefficients).

Tab. 1: LS coefficients (in bold significant coefficients).

Intercept = **-0.095**	C1 = **0.041**	C2 = **0.021**	C3 = 0.013	C4 = **0.022**
D1 = **0.031**	D2 = **0.283**	D3 = **0.247**	D4 = **0.048**	D5 = **0.129**
D7 = **0.099**	D10 = **0.087**	E1 = **0.007**		

It is well known that each LS coefficient measures the change in the conditional mean of the overall satisfaction deriving from a change in the assessment of each course feature fixing all the others. From a first analysis of the coefficients, it results that the main impact on the satisfaction is played by D2 (interest attraction capability of the teacher), D3 (clearness of the teacher) and D5 (suitable materials for studying). Although informative with respect to the central part of the conditional distribution of the response variable, conditional mean regression models are not able to study the different effects (in sign and quantity) at the different locations of the conditional distribution of the student satisfaction. At this aim a global analysis exploiting quantile regression is proposed in the next Section.

3. QUANTILE REGRESSION: METHODOLOGICAL ISSUES AND MAIN RESULTS

Quantile regression (QR), as introduced by Koenker and Basset (1978), may be considered an extension of classical least squares estimation of conditional mean models to the estimation of a set of conditional quantile functions. Quantile regression allows indeed to estimate the conditional quantiles of a response variable (**y**) as a function of a set **X** of covariates. Although different functional forms can be used, the paper restricts to linear regression models and it uses a semi-parametric approach in the sense that no parametric distribution assumptions are required for the error distribution, while an assumption is used in order to specify the functional form of the model.

The QR model for a given conditional quantile θ can be formulated as follows:

$$Q_\theta(\mathbf{y}|\mathbf{X}) = \mathbf{X}\beta(\theta) \tag{1}$$

where $0 < \theta < 1$ and $Q_\theta(.|.)$ denotes the conditional quantile function for the θ^{th} quantile. The parameter estimates in QR linear models have the same interpretation as those of any other linear model: each $\beta_i(\theta)$ coefficient can be interpreted as the rate of change of the θ^{th} conditional quantile of the dependent variable distribution per unit change in the value of the i^{th} regressor:

$$\beta_i(\theta) = \frac{\partial Q_\theta(\mathbf{y}|\mathbf{X})}{\partial \mathbf{x}_i} \tag{2}$$

In the proposed empirical analysis, quantile regression capabilities are exploited to identify the impact that each feature of a course has on the different levels of the SS. In Figure 1, LS and QR coefficients corresponding to the different course features are graphically represented in the panels of the graph. It is worth to remind that LS coefficients measure a change in the conditional mean while QR coefficients measure a change on a given conditional quantile. The horizontal axis in each panel displays the different quantiles while the effect of each feature holding the others is represented on the vertical axis. The solid line and the dashed lines parallel to the horizontal axis correspond to LS coefficients and to their confidence intervals, respectively. The grey area in each panel shows the confidence interval for the different conditional quantiles. Figure 1 can be useful to explore from a descriptive point of view the coefficient trends along the different quantiles and to compare the effects highlighted by QR with respect to the unique LS detected effect.

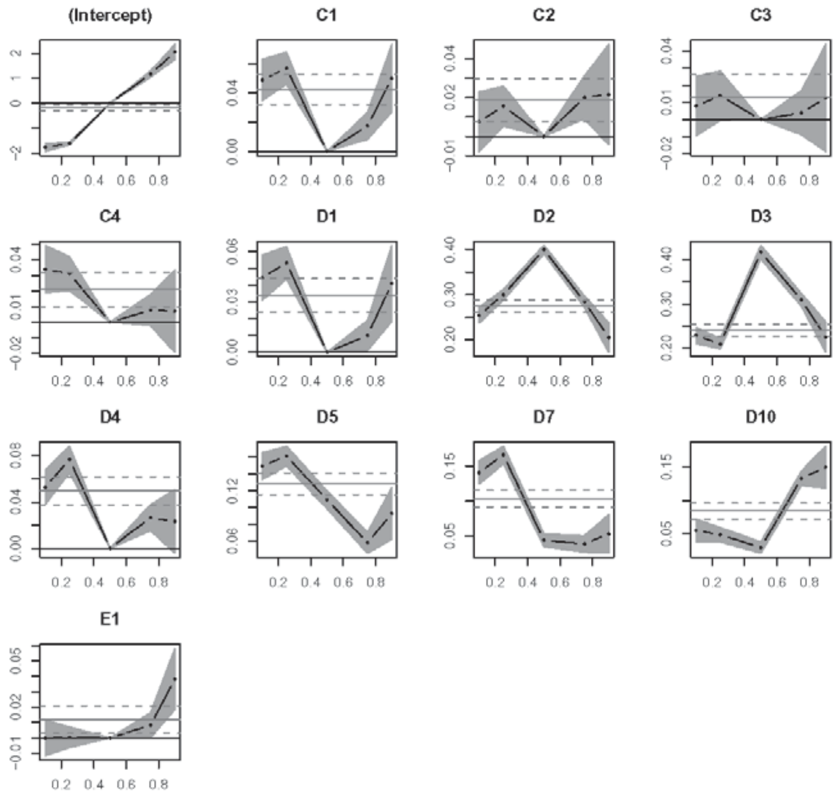

Fig. 1: LS and QR results: x-axis depicts the different conditional quantiles. In each panel the horizontal lines show the LS coefficients (solid line) and the corresponding confidence interval (dashed lines). Grey area is instead used to show confidence intervals of the QR coefficients.

In order to take into account the generalization capability of the model, the coefficients estimated by QR (the following quantiles are considered: 0.1; 0.25; 0.5; 0.75; 0.9) are shown in Table 2 highlighting in bold significant coefficients at α=0.1.

For a better description of the conditional quantiles, a grid of 100 quantiles ($\theta = 0.01$ to 0.99 with a step of 0.01) has been considered. The obtained results are graphically described referring to the different sections or subsections of the questionnaire. Let us consider in Figure 2 the coefficients of the questions D2 (interest attraction capability of the teacher), D3 (clearness of the teacher) and D10 (interaction with the teacher during lessons). All these features are related to teaching aspects.

As in the previous figure, the horizontal axis displays the different quantiles

Tab. 2: QR results for five conditional quantile. Significant coefficients at α=0.1 are in bold.

variable	$\theta = 0.10$	$\theta = 0.25$	$\theta = 0.50$	$\theta = 0.75$	$\theta = 0.90$
Intercept	**-1.775**	**-1.612**	0.000	**1.165**	**2.048**
C1	**0.049**	**0.057**	0.000	**0.017**	**0.050**
C2	0.007	0.015	0.000	**0.020**	0.021
C3	0.008	0.014	0.000	0.004	0.012
C4	**0.034**	**0.031**	0.000	0.008	0.007
D1	**0.044**	**0.053**	0.000	0.010	**0.041**
D2	**0.254**	**0.300**	**0.400**	**0.285**	**0.205**
D3	**0.228**	**0.210**	**0.417**	**0.310**	**0.225**
D4	**0.053**	**0.077**	0.000	**0.026**	**0.023**
D5	**0.150**	**0.162**	0.109	**0.058**	**0.093**
D7	**0.141**	**0.166**	0.044	**0.039**	**0.053**
D10	**0.055**	**0.048**	0.029	**0.133**	**0.150**
E1	0.000	0.000	0.000	0.008	**0.038**

while the coefficients are represented on the vertical axis. Coefficients stand for the effect of each course features holding the others constant. From the analysis of Figure 2, it is evident the added value of quantile regression: for unsatisfied students (left part of Figure 2), D2 has the main impact on the satisfaction followed by D3 and D10; for satisfied students, instead, the ranking of the first two questions is reversed (i.e. the importance ranking becomes: D3, D2, D10).

Using QR results it is then possible to order each course feature according to its impact on the satisfaction thus identifying the strategic levers for the improvement of satisfaction. Moreover, taking into account that classical LS regression provides a unique coefficient for each feature, QR can offer a useful complement to standard analysis, allowing a discrimination among cases that would be otherwise judged equivalent using only conditional expectation. At this aim, let us consider the LS coefficients in Table 1 for the questions C2 (schedule of the course) and C4 (co-ordination with other courses), which are almost identical (0.021 and 0.022 respectively). The corresponding QR coefficients, along with the others coefficients related to the course design features, are shown in Figure 3. C2 and C4 change their seats with respect to their role on the global satisfaction. Unsatisfied students attribute more importance to C2 (the corresponding dashed line lies above the C4 dot–dash line for values of θ up to 0.4). For the central quantiles (from 0.4 to 0.6) the two lines are overlapped confirming LS results. The situation

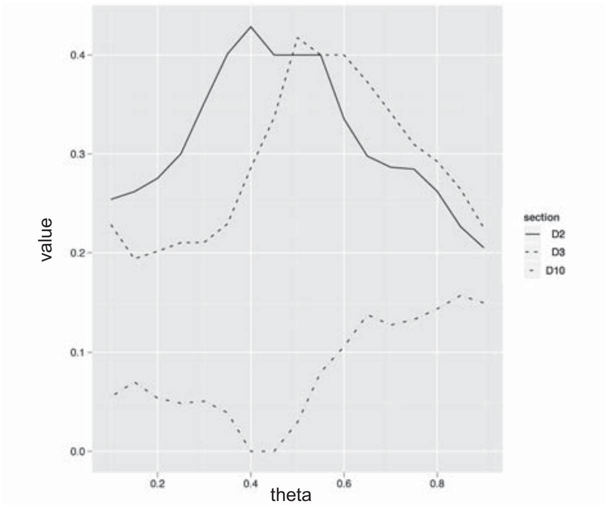

Fig. 2: QR coefficients for the teaching features. The x-axis shows the different conditional quantiles while coefficients are depicted on the y-axis.

reverses for the quantiles pertaining to the upper conditional quantile distribution (satisfied students).

Moreover, Figure 3 allows to visually catch that the four considered features play no role on the overall satisfaction in the central part of the response variable distribution while the importance of each of them changes in lower and upper quantiles. Furthermore, for unsatisfied students, C1 (conditions to take exams) has the main impact on satisfaction followed by C2 (schedule of the course), C3 (availability of the teacher) and C4 (co-ordination with other courses) while for satisfied students C2 is the most important feature followed by C3, C1 and C4. The null effect in the central part of the conditional distribution can be related to the classical concentration of the responses on the central part of the scale (Likert 1932) .

The estimation of conditional densities of student satisfaction can be an useful tool to go more in depth on the effect of a given regressor and to try to explain the null effect in the central part of the response variable distribution. Exploiting the quantile regression estimates, indeed, it is straightforward to estimate the student satisfaction conditional distribution as follows:

$$\widehat{\mathbf{y}}_\theta = \mathbf{X}\widehat{\beta}\,(\theta) \tag{3}$$

for $0 < \theta < 1$.

It is obvious that the estimated conditional distribution is strictly dependent on the values used for the covariates. In order to evaluate the effect on the conditional SS, a what–if analysis can be then carried out simulating different scenarios

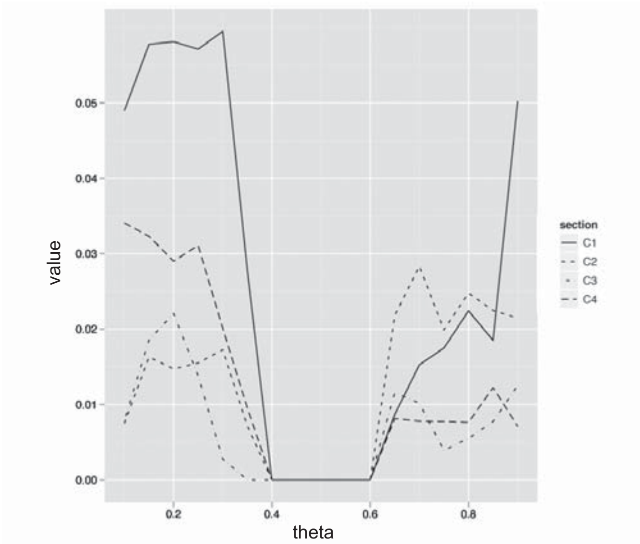

Fig. 3: QR coefficients for the Course design features.

by changing values of covariates in equation (3). For instance, in order to try to explain the null effect of C1 in the central part of the distribution, four different profiles are defined supposing that the score for each question is equal to 3 except for C1 that assumes values 2, 5, 7, 10. The obtained densities are showed in Figure 4. It is worth of notice that in the central part of the distribution nothing changes for the different values of C1 while differences appear in case of low and high values.

Considering another covariate, D3, for which the null effect is not present (see Figure 2), it is possible to appreciate the information provided by conditional densities. At this aim, the four previous profiles are modified using the same value 3 for all the variables except for D3 that assumes values 2, 5, 7, 10. Figure 5 shows strong differences among the four conditional distributions both in shape and in location.

A further example of the usefulness of the conditional density estimates is provided by the use of extreme profiles; in particular, density estimation analysis is used to identify how much the evaluation of the global satisfaction is coherent with the judgments concerning all the features of a course. The extreme profiles are defined using uniform judgments for all the considered features: an unsatisfied profile corresponds to judgments equal to 2 for all the variables while, on the opposite side, a student expressing scores equal 10 on all the different features represents an extreme satisfied profile. The other two considered profiles contains all values equal to 5 or 7. The analysis of the obtained histograms (Figure 6)

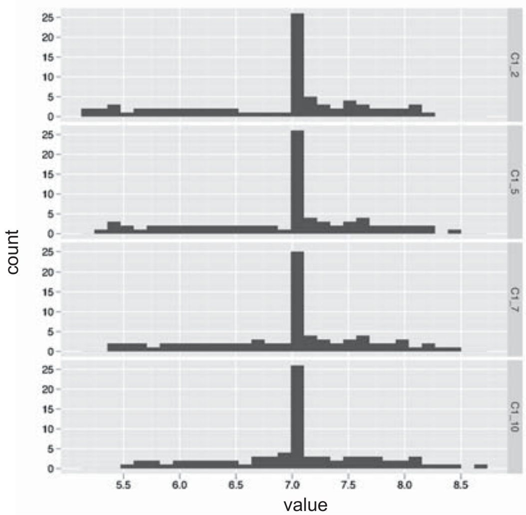

Fig. 4: Density estimation of SS corresponding to the defined scenarios. The densities are obtained using scores equal to 3 for each question but for C1, which assumes values 2, 5, 7, 10.

reveals that, in case of high scores, the distribution is more concentrated than in case of low scores, showing a strict coherence among the final score and the feature scores in case of satisfied students. On the contrary, unsatisfied students are more heterogeneous in the final score. It is worth to notice that overlapping regions are present both between profile 1 (Score_2) and profile 2 (Score_5) and between profile 2 (Score_5) and profile 3 (Score_7). Such behavior suggests that suitable policies should allow to move students from profile 1 to profile 2 and students from profile 2 to profile 3.

4. TYPOLOGY IDENTIFICATION: METHODOLOGICAL ISSUES AND MAIN RESULTS

The QR analysis provided in Section 3 is not able to highlight possible differences in the dependence structure of SS among units. At this aim a potential use of QR is here offered. The proposal exploits QR to detect a typology and it can be used in a twofold way embedded in an unsupervised and/or a supervised framework. The former allows to group units with similar behavior and the latter permits to verify the existence of significant differences among prior defined groups. In both the cases, once the typology is identified, different QR coefficients for each group can be estimated.

The proposed approach begins with the identification of the 'best' QR model for each statistical unit, simply choosing the quantile that provides a value of $\hat{y}_{i\theta}$

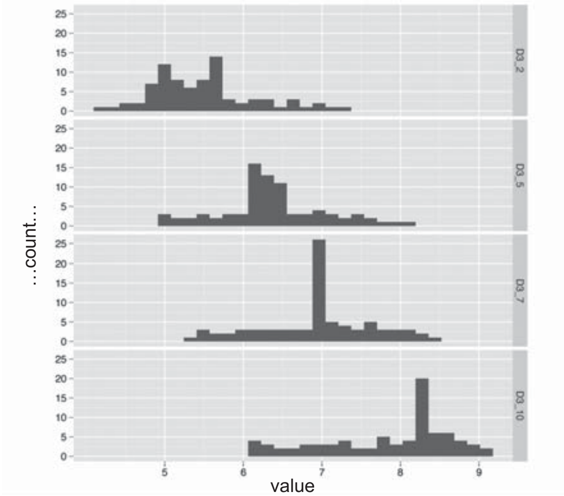

Fig. 5: Density estimation of SS corresponding to different profiles for the clearness of the teacher.

closer to the observed response variable. Let us refer to equation 3: $mat\hat{h}bf\,\hat{\mathbf{y}}_\theta$ is computed for a dense grid of quantiles (θ varying form 0.01 to 0.99 with a step of 0.01); for each statistical unit the best model is then selected as the one minimizing $|y_i - \hat{y}_{i\theta}|$. Let us denote with $(\hat{\mathbf{y}}_{\theta_{BEST}})$ the reconstructed response variable and with θ_{BEST} the corresponding vector of quantiles associated to the statistical units. The added value in considering the reconstructed estimated response variable $(\hat{\mathbf{y}}_{\theta_{BEST}})$ instead of a LS estimated response variable is evident from Figure 7.

Units can be grouped according to the best quantile (θ_{BEST}) they have been assigned because it can be considered as an indicator of a similar dependence structure. Different criteria can be followed to identify the clusters. In the following a very simple solution is adopted by grouping units in four classes according to the values of θ_{BEST}: (0,0.25]; (0.25,0.5]; (0.5,0.75]; (0.75,1]. For each group, the average quantile can be considered as the group reference quantile. In Table 3 the percentage distribution of units and the reference quantile for each group (average quantile) are shown.

Tab. 3: Percentage frequency distribution of the identified typology and group reference quantiles.

group	% of units	reference quantile
(0,0.25]	20,4%	0.126
(0.25,0.5]	28,5%	0.374
(0.5,0.75]	32,9%	0.618
(0.75,1]	18,2%	0.922
Total	100,0%	

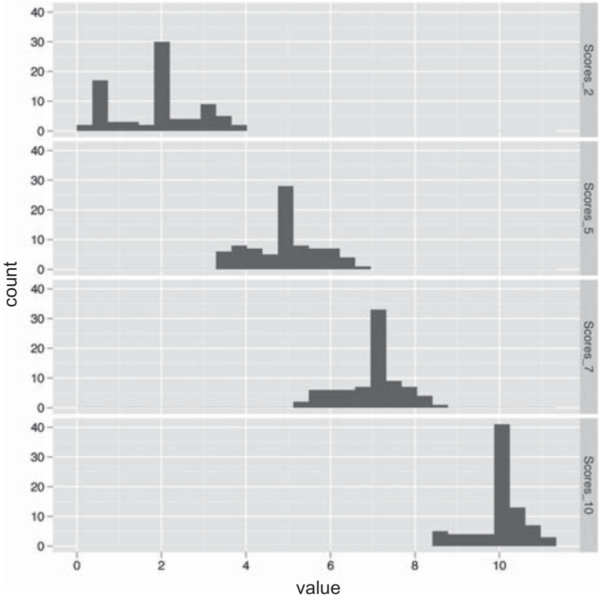

Fig. 6: Histograms of SS conditional densities corresponding to extreme uniform profiles.

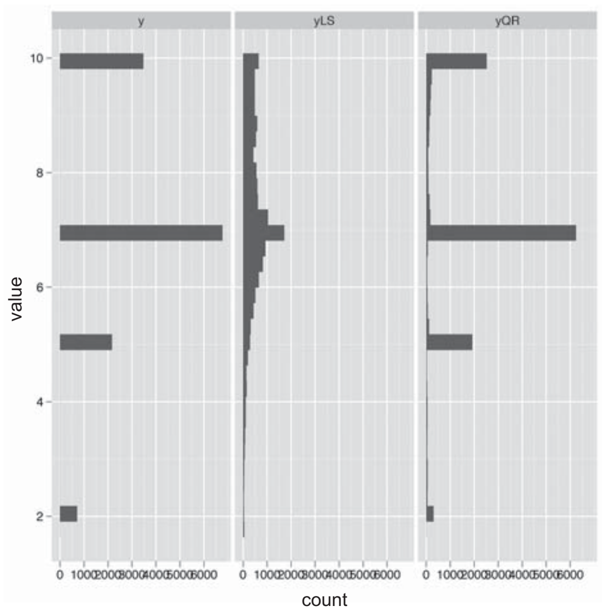

Fig. 7: Comparison among the original SS distribution (left panel), LS estimated response variable (middle panel) and QR estimated response variable (right, panel) by selecting the 'best model' for each statistical unit.

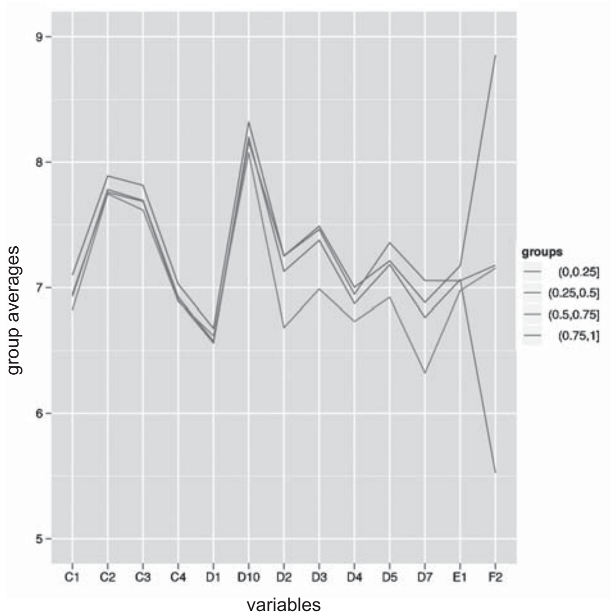

Fig. 8: Average values of the regressors for each group.

Differences among groups can be explored from a descriptive point of view analysing the average values of the regressors for each group (Figure 8). In order to summarize differences among groups in the dependence structure, QR is again executed only retaining the reference quantiles: the resulting coefficients should synthesize the different behavior of the groups with respect to the dependence structure among SS and course features. In Figure 9, QR coefficients are graphically represented for the different regressors and for each group. The different panels refer to the four groups while each bar depicts the value of the coefficient related to the considered regressor. In such a way it is possible to visually catch the different effect of course features on the SS variable for the four groups. The first group, for instance, is characterized by high coefficients for most of the variables, while students belonging to the second and third group show that only some course features determine the global satisfaction level. Finally, in the fourth group the different course features play a role on the global satisfaction, although only a limited set of them appears to exercise strong influence.

As stated before, the proposed approach is also suited if an a priori grouping variable is available. In such case, the goal is to explore if SS varies according to the levels of such a grouping variable. With respect to the student satisfaction analysis, Faculty membership can be used as grouping variable. The simplest solution could consist in estimating different models for each considered quantile

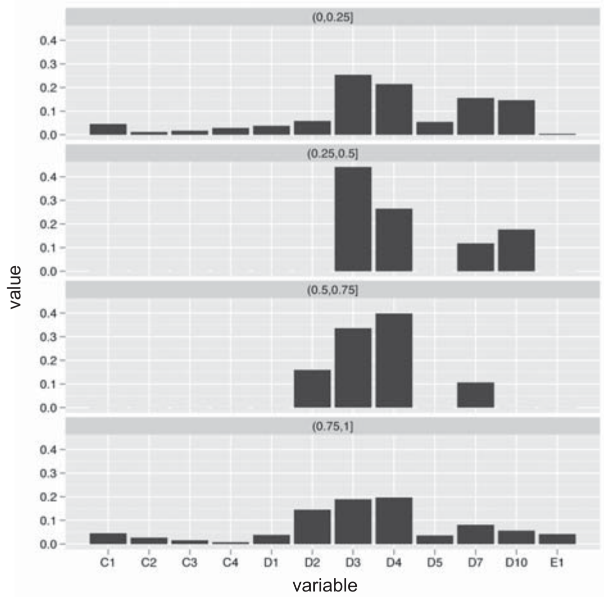

Fig. 9: QR coefficients for the different course features (bars) and for the different groups (panels).

and for each Faculty. However the estimation of different models is unsatisfactory as a global view is missing and it is not easy to compare the different models. Such problems cause difficulty in evaluating the impact of each Faculty on the global satisfaction.

A different solution, quite common in the literature, relies on the introduction of a dummy variable in the global analysis. This approach is able to modify the intercept of the model according to the Faculty membership, catching so the effect of each level but it does not provide the impact of the different levels on the explanatory variables.

A different solution is provided following the approach proposed in this Section. Once the best quantile is assigned to each unit, a reference quantile for each level of the grouping variable (Faculty) can be identified as the average $(\hat{\mathbf{y}}_{\theta_{BEST}})$ taking into account only the units belonging to that level.

In Figure 10 the distribution of the best quantiles $(\hat{\mathbf{y}}_{\theta_{BEST}})$ assigned to units is shown for each group, i.e. for the considered six Faculties. Different panels of the Figure refer to Faculty membership. It is worth of notice that the six distributions are quite similar thus providing averages of the best quantiles as much similar: $\bar{\theta}_{BEST_{SP}} = 0.459$, $\bar{\theta}_{BEST_{ECO}} = 0.482$, $\bar{\theta}_{BEST_{GIU}} = 0.503$, $\bar{\theta}_{BEST_{SC}} = 0.470$, $\bar{\theta}_{BEST_{SF}} = 0.463$, $\bar{\theta}_{BEST_{LEF}} = 0.478$.

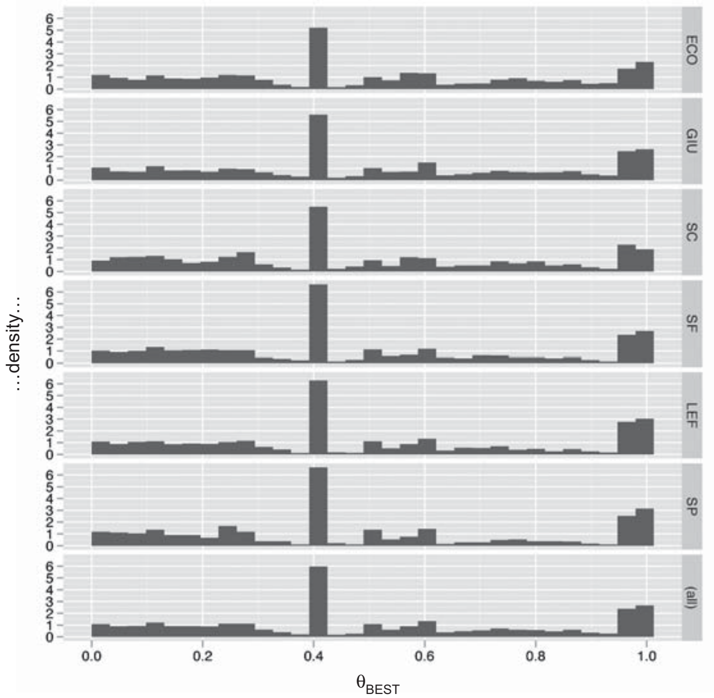

Fig. 10: $\hat{\theta}_{BEST}$ distribution for the different levels (panels of the graphs) of the a priori grouping variable and for all the units (last panel).

Finally, estimation of the QR model using the reference quantiles is executed: the resulting coefficients should be able to catch the impact on the response variable (SS) of the levels (Faculties) of the grouping variable for each regressor. As the distributions of the best quantiles for each group and for all the units are not so different (Figure 10), the estimation of QR models for the different levels of the stratification variable leads to a similar dependence structure for the different levels. Therefore, the obtained results are pretty much the same with global QR model using a value of $\theta = 0.5$ (see Figure 1).

5. CONCLUDING REMARKS

The aim of the paper is to measure student satisfaction in order to help institutions to pinpoint the strengths of educational processes and to identify areas for improvement. In order to grasp the complexity of the learning experience, it is not enough to know the degree to which students are satisfied but it is important to understand the factors that determine student satisfaction.

Quantile regression is a useful complement to standard analysis, allowing discrimination among cases that would be otherwise judged equivalent using only conditional expectation. Exploring the whole conditional distribution of the dependent variable, it is possible to identify suitable strategic levers for different degrees of satisfaction.

Quantile regression offers then a more complete view of the relationships among variables, providing a method for modeling the rates of changes in the response variable at multiple points of its conditional distribution. As the independent variables could affect the response variable in different ways at different locations of its conditional distribution, useful insights derive from extracting information at other places other than the expected value. Furthermore, QR does not require any parametric assumption for the error distribution.

The obtained QR estimates are also used for a what–if analysis by simulating different scenarios for the regressors and estimating the corresponding conditional distribution for the global satisfaction. Such approach offers useful insights in order to tune proper policies able to move students toward higher levels of satisfaction.

Finally, an innovative solution is proposed to analyse grouping effects. The solution is suitable both in an unsupervised clustering and when an a priori group variable is available.

Further development would include the exploration of the statistical significance of the differences among coefficients estimated for the different groups. Moreover, a sensitivity analysis could be carried out to evaluate how much the obtained results depend from some choices of the researcher (i.e. quantification of the variables, number of considered quantiles, way to compute the reference quantile.

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LA REGRESSIONE QUANTILE PER LA VALUTAZIONE DEL LIVELLO DI SODDISFAZIONE DEGLI STUDENTI UNIVERSITARI

Riassunto

Il lavoro si inserisce nel contesto della valutazione dei processi formativi ed in particolare della misurazione dell'efficacia interna attraverso la soddisfazione degli studenti frequentanti. L'obiettivo è misurare la soddisfazione degli studenti frequentanti tenendo conto che l'effetto delle principali caratteristiche di un corso può essere differente per gli studenti soddisfatti e per quelli insoddisfatti. L'analisi è stata condotta utilizzando la regressione quantile che permette di stimare l'effetto delle variabili esplicative sui diversi quantili condizionati della variabile dipendente, offrendo informazioni sull'intera distribuzione condizionata e non sulla sola posizione centrale. Le stime ottenute permettono, inoltre, di condurre un'analisi di tipo what–if al fine di orientare le opportune politiche volte ad aumentare il livello di soddisfazione degli studenti. Una soluzione innovativa è, infine, proposta per valutare la presenza di differenti gruppi di studenti. Tale proposta può essere utile sia nel caso di un approccio di classificazione di tipo non supervisionato che quando è disponibile una variabile di stratificazione nota a priori.