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# DRIVERS AND UNCERTAINTY FOR JOB SATISFACTION OF THE ITALIAN GRADUATES

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***Abstract.*** *Education outputs are detected through a large number of statistical tools suitable to support policy design of governing authorities and decision making process of stakeholders. Several proposals have emerged to outline the aspects that mostly shape the composite concepts of both courses evaluation and internal/external effectiveness, considered as multifaceted latent constructs, such as graduates well-being at work. This paper aims at studying job satisfaction of a large sample of Italian graduates (Master of Arts) through an innovative framework for ordinal data modelling, which allows to take into account both feeling/satisfaction and heterogeneity/uncertainty in response patterns. The effects of significant subjective and structural covariates on self-declared assessments are considered as prominent job satisfaction drivers and a comprehensive model which includes past evaluations is examined. Data stem from the AlmaLaurea XVII Survey on Italian graduates' working conditions carried out in 2014.*

***Keywords:*** *Job satisfaction, AlmaLaurea XVII Survey, Ordinal data, Mixture models.*

## 1. INTRODUCTION

In the last few decades there has been a worldwide development of the studies emphasizing practices and performances of higher education (Lockheed and Hanushek, 1994, among others). In this respect, different statistical tools deal with evaluation in its diverse expressions (Attanasio and Capursi, 2011; Bacci and Gnaldi, 2015; Bird et al., 2005; Grilli and Rampichini, 2009, among many others), and manifold aspects may be considered in education and labour market studies. Mostly referring to the Italian context, it is a mandatory duty for the involved institutions to assess the outputs of tertiary education (Cammelli and Gasperoni, 2012), as it is in many other European higher education systems. More specifically,

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with a focus on its external features, university effectiveness can be measured in a number of ways in different contexts, depending on time and actors (Corduas et al., 2009; Fabbris, 2012). As an instance, very simple performance indicators may be derived from labour market figures and other administrative data. A suitable indicator of external effectiveness, in terms of employability outcomes, may be the inverse function of the time necessary to find the first occupation after graduation (Campostrini and Gerzeli, 2007). The quota of graduates who are employed shortly after their graduation may be interpreted as a measure of *attractiveness*, that is a proxy of the effectiveness of their university curriculum in the competitive labour market. On the other hand, this proportion can be determined not only by the intrinsic quality of the education but also by the surrounding social and economic environment. As a matter of fact, assessing university outcomes only through labour market indicators may be misleading, since graduates' employability is extremely influenced by local conditions and economic conjuncture (Campostrini and Gerzeli, 2007; Folloni and Vittadini, 2010).

Without neglecting the macroeconomic objectives of increasing employment levels, achieving a "fulfilling employment" allows for working conditions that favour personal growth, individual well-being and autonomy. Some studies (Schomburg and Teichler, 2006) show how the disciplinary field of studies is decisive for job satisfaction. Prominent differences are highlighted with respect to gender (such as, for instance, the male prevalence in the choice of technical-scientific paths), sector of activity and social context. The segmentation linked to the choice of the "field of study" is the one that revealed the greatest impact, both with respect to better matching and with regard to life satisfaction in general and job satisfaction in particular (Vila et al., 2007).

Furthermore, working conditions undoubtedly influence subjective well-being and, as it is natural and tautological, the very fact of having a job constitutes a prerequisite to experience good conditions in the professional sphere. The wide literature on working conditions and on the multiple meanings that workers derive from the concept of work itself - recognizes that work provides tangible "rewards" and "intangible" compensations (Budd, 2011).

With reference to working conditions of graduates during the recent economic crisis, in many Western countries comparable results emerge (Switek, 2013). Taking into account the first employment of graduates from some US universities, the individuals with tertiary education who enter the labour market in a context of crisis seem to be more satisfied with their job as compared to those who have met better economic conditions (Bianchi, 2013). Non-dissimilar findings for the same period arise from the survey on the professional integration of graduates which is carried out by the Italian National Institute of Statistics (ISTAT) in order to understand conditions and employment pathways of those who have completed a degree course (Iammarino and Marinelli, 2011).

For some authors, when detecting graduates' performances in the labour market, non-cognitive learning achievements deserve prominent attention (Martini and Fabbris, 2017). Moreover, in a framework considering human and social capital (Fabbris and Favaro, 2012; Ferrante, 2014; Muñoz de Bustillo et al., 2011; Ricci, 2011) it is not uncommon to point out the relevance of perceived quality of working life and the role of job satisfaction as proxies of the overall well-being as a further indicator of university effectiveness (Oshagbemi, 2003).

Also, research interests referred to education premium have been spread in a wide range of fields and now involve objective measures of the education investments (such as employment returns in terms of salary, professional status and career prospects, for instance) as well as individuals' career self-evaluation (Boccuzzo and Paggiaro, 2012). When the educational costs are considered (Verhofstadt et al., 2007; Weiss, 2002) the role played by job satisfaction is often stressed as a job quality predictor. Globally, the analysis of individual returns of education investments indicate that higher levels of education are related to higher income, lower risk of unemployment and promising career prospects. The positive correlation between level of education and income is a common structural feature in all the developed countries (OECD, 2018).

In recent years, however, and especially in Italy, there seems to be a reversed trend: investment in education has proved less profitable than in the past (Ferrante, 2014). The evidence of an inverse relationship between level of education and job satisfaction is frequent in education economics literature (Muñoz de Bustillo et al., 2011). Scholars are interested in understanding the reasons why individuals use to make such an effort in their own education if they are not eventually compensated with a good job. However, despite of the abundance of studies aimed to assess the impact of the university choice on labour income (Black and Smith, 2006, among many others), little is known about the effects of university education on nonpecuniary aspects of life. Job satisfaction does not seem to grow comparatively with achieved degrees and, indeed, overeducation and educational mismatch may result in a non-optimal allocation of human capital and in a source of frustrations (Boccuzzo et al., 2016; Green and Mcintosh, 2007; Green and Zhu, 2010). In this context, especially within the Italian labour market, the role played by graduates with respect to entrepreneurship and innovation is another prominent topic of research (Bugamelli et al., 2012; Visco, 2014, among others). According to this line of reasoning, suitable effectiveness measures on job satisfaction may be worth of interest to various governing authorities and stakeholders, even controlling for the study field (OECD, 2012; Vila et al., 2007). While maintaining an inherently *individual* nature of the responses, these measures may provide useful information on different aspects in a subjective perspective, since we refer to statements of self-declared contentment/fulfilment.

This work examines the evolution of job satisfaction with regards to a large sample of Italian Master of Arts graduates, interviewed by AlmaLaurea Consortium during 2014 Survey (AlmaLaurea, 2015). Specifically, job satisfaction expressed at 1, 3 and 5 years after graduation by the same respondent has been collected. Then, a class of mixture models able to take into account both the level of self-assessed satisfaction and the inherent heterogeneity in the response patterns has been introduced in order to achieve both simple interpretation and effective graphical visualization of results. As for any synthetic measure, such models are to be examined in light of both individual and context drivers.

Undoubtedly, the sample design includes a possible selection bias (Heckman, 1979; Wooldridge, 1995) that might be caused by different circumstances: first, only graduates who are employed after 5 years are considered; second, only those who accepted to be interviewed have been considered in the sample hereafter analysed; third, only individuals who responded to all the three questionnaires are examined. Given the available set of information, those bias components are unavoidable and their effects can be evaluated only ex-post, by considering the socio-demographic structure of the sample. As summary statistics will confirm, respondents can be considered as sufficiently representative of the population in the examined data set (AlmaLaurea, 2015).

The paper is organized as follows: data and methods are illustrated in Sections 2 and 3, respectively, whereas Section 4 shows the effects on job satisfaction of drivers pertaining to different domains, first by separate analysis and then by a global model. Section 5 discusses the evolution of satisfaction along the three waves and Section 6 motivates a comprehensive model with a discussion of relative performances. Some concluding remarks end the study.

## 2. DATA DESCRIPTION

Data of interest stem from the archive of AlmaLaurea, an Inter-University Consortium including 72 out of 77 public Italian Universities (telematic Universities and Schools of advanced studies are excluded). Graduates are usually interviewed at 1, 3 and 5 years after degree to monitor their carriers: the subset of data here considered concerns only those graduates in 2009 that were employed at the time of all the three interviews. The survey has been carried out in 2014; thus, it refers to the population of Italian MA graduates[2] in 2009. All the fields of study have been examined but Armed Force degrees, given their limited size (AlmaLaurea, 2015).

AlmaLaurea archive in 2014 covered 65.7% of all the Italian graduates. Those interviewed 1, 3, 5 years after degree are 59.4%, 52.4% and 46.4% of the initial sample, respectively. The final sample consists of respondents who declared to be employed (or self-employed) in all three occasions and answered the items of interest, representing 40.4% of 2009 graduates. This sample attrition is unavoidable, given several circumstances: changes of residence, refusals, incomplete or inconsistent interviews, losing and/or obtaining a job in the examined period, and so on. Thus, final considerations and remarks should be mitigated since they refer to employed graduates who were also willing to answer in all the three waves.

Interviewees have been administered CATI-CAWI questionnaires and their responses to the item concerning job satisfaction have been collected on a 10 point ordinal scale (1 meaning “extremely dissatisfied” and 10 “extremely satisfied”). All the statistical analyses are performed using a modified 9 point scale: in fact, in order to limit some response style effects (Capecchi and Piccolo, 2016), frequencies of 9 and 10 scores have been aggregated since those extreme evaluations have been treated as “extremely satisfied”. Given the limited number of missing values in some covariates, a list-wise omission approach has been adopted: then, all the computations and models concern $n$ = 17154 observations.

Women are the majority (58%) of those interviewed and 86% of respondents hold a full time job; 27% work in the public sector. The age at graduation ranges from 22.40 to 64.21 years (the average is 28.37 and median is 26.15 years, so a positive skewness is observed); about 8% of respondents were over 40 years when they got their degree, and about 300 of them were older than 50. The graduation mark – which in the Italian system varies from 66 to 110 *summa cum laude*, here computed as 112 – is on average 106.7 with a median of 109. Indeed, this distribution is highly positively skewed since the last two marks (110 and 110 *cum laude*) includes 48% of the sample.

With reference to the competences achieved at University, only half of the respondents provide a “positive” answer, whereas more satisfactory are the results concerning the effectiveness of the studies. In this regard, the effectiveness of the degree, which synthesises two important aspects related to the usefulness and exploitability of the degree on the labour market, respectively, derives from the

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[2] MA here refers to both “Laurea magistrale” and “specialistica”, and “Laurea magistrale a ciclo unico”.

combination of questions concerning the use of the competences acquired at university and the necessity (both formal and substantial) of the academic qualification for the job activity. Thus, five ordinal levels of effectiveness can be distinguished; accordingly, a score is attributed varying from “very effective” (=5) to “ineffective” (=1). Then, 60% declared that their studies were “very effective” or “effective” and only 6% selected the “ineffective” category (AlmaLaurea, 2015).

Special attention will be devoted to job satisfaction at 5 years after graduation since it may be considered a more consolidated evaluation of personal fulfilment with respect to the work environment. Indeed, when comparing expressed satisfaction across interviewees at 1, 3 and 5 years, a reduction in variability along the waves is observed.

Since the sample consists of longitudinal observations, time and subjects relations should be taken into account. In this respect, literature includes different methods to deal with such topics: marginal models, regression with fixed and random effects, trajectories analysis, transitional models (Baltagi, 2008; Cagnone et al., 2009; Frees, 2004; Hsiao, 2003, among others). Here, a class of mixture models useful to disentangle the main components which drive the expressed satisfaction is considered and flexible specifications are exploited to investigate the changes in job satisfaction and its main drivers.

In addition, further considerations might be added: as an instance, responses are collected ignoring the hierarchical structure of graduates who attend the same universities and whose similar experiences are generally correlated. Given dataset information this aspect, that deserves closer examination by multilevel modelling approaches (Grilli and Rampichini, 2009), is not pursued in this paper.

## 3. A CLASS OF STATISTICAL MODELS

Job satisfaction is a personal evaluation where both subjective and objective factors are involved with several aspects of life-course and work-related issues. When graduates are asked to express their perception about this item on a scale, empirical evidence shows that the expressed rating is the result of a weighted assessment between a psychological reaction (attraction, indifference, aversion) and an inherent indecision affecting any human choice (often, related to the circumstances surrounding the response). Then, a mixture model may be legitimate and several statistical considerations lead to the shifted Binomial and discrete Uniform distributions, respectively, to represent the two factors affecting the choice (Piccolo and Simone, 2019, section 2). Those components are intrinsically present in the model specification and, given the availability of suitable information, may be checked if related to a set of subjective and contextual covariates.

Formally, for a given $m > 3$ ordinal categories, the response $R_i \in \{1, 2, \dots, m\}$ of the $i$-th interviewee is interpreted as a convex combination of a genuine satisfaction for the job and an intrinsic indecision. Then, CUB models (D'Elia and Piccolo, 2005; Piccolo, 2003) have been introduced as a *C*ombination of a discrete *U*niform and a shifted *B*inomial for the second and first components, respectively, that is:

$$\begin{cases} Pr(R_i = j) = \pi_i \binom{m-1}{j-1} \xi_i^{m-j} (1-\xi_i)^{j-1} + (1-\pi_i)\left(\frac{1}{m}\right), \; j = 1, 2, \dots, m; \\ \pi_i = \pi_i(\boldsymbol{\beta}) = \dfrac{1}{1+e^{-\boldsymbol{y}_i \boldsymbol{\beta}}}; \qquad \xi_i = \xi_i(\boldsymbol{\gamma}) = \dfrac{1}{1+e^{-\boldsymbol{w}_i \boldsymbol{\gamma}}}; \quad i = 1, 2, \dots, n. \end{cases} \tag{1}$$

To improve interpretation, the systematic relationships in (1) may be expressed as:

$$\begin{cases} logit(1-\pi_i) = -\boldsymbol{y}_i \boldsymbol{\beta} = -\beta_0 - \beta_1 y_{i1} \dots - \beta_p y_{ip}; \\ logit(1-\xi_i) = -\boldsymbol{w}_i \boldsymbol{\gamma} = -\gamma_0 - \gamma_1 w_{i1} \dots - \gamma_q w_{iq}; \end{cases} \quad i = 1, 2, \dots, n; \tag{2}$$

where $y_i$ and $w_i$ are the row vectors of the values for the $i$-th subject of the covariates which have been selected to explain satisfaction and uncertainty, respectively. The direction and the weight of each covariate on the response components of feeling and uncertainty are emphasized by just considering the corresponding parameters $\beta$ and $\gamma$.

The flexibility and parsimony of CUB models to capture different shapes of distributions and the ability to interpret data features by means of a graphical representation of the estimated models are appealing characteristics of this approach. Specifically, for any subject, model (1) implies a bijective correspondence with points ($1 - \pi_i$, $1 - \xi_i$) in the parameter space (that is a unit square) so that the interpretation of the covariates effect is made immediate. The representation of the whole distribution by just a sequence of points is a strong simplification for interpreting the model with respect to the intrinsic components and, when present, to significant explanatory covariates. In this way, the relative position of the estimated models in the parameter space is immediately comparable in terms of feeling and uncertainty, respectively.

Notice that whereas ($1 - \xi_i$) are direct measures of job satisfaction, the parameters ($1 - \pi_i$) are expression of both respondents' indecision and heterogeneity among the clusters to be considered. As a matter of fact, when almost all the respondents are very resolute they provide similar scores and thus heterogeneity is very low; on the contrary when heterogeneity is high, respondents select quite different categories thus manifesting larger uncertainty.

An added value of the approach is the possibility to examine preference data without the need to refer to subjects' covariates; thus, the graphical representation of the estimated models for different clusters, situations, circumstances, etc. is able to compare the whole observed distributions by just contrasting the corresponding points in the parameter space.

Several variants and extensions of CUB models have been developed and most of them are fully summarized in Piccolo and Simone (2019); in addition, an accurate comparison with more consolidated cumulative models (Agresti, 2010; Tutz, 2012) has been pursued, on the basis of logical foundations, simulation results and empirical evidence (Piccolo et al., 2019). Computations and inferential results for this class of models –based on asymptotically efficient maximum likelihood procedures obtained with EM algorithm (Piccolo, 2006)– are implemented in the R package CUB, which is available on CRAN (Iannario et al., 2018).

Given the nature of the responses, it is possible to confront job satisfaction expressed by each *i*-th graduate 1, 3 and 5 years after graduation; these ordinal evaluations have been denoted as $S_i^{(1)}$, $S_i^{(3)}$, $S_i^{(5)}$, respectively. Their distributions are strongly skewed towards high values since only few graduates reported intermediate or high levels of dissatisfaction. In fact, the frequency distributions of responses seem quite similar (left panel of Fig.1).

The corresponding CUB models (as depicted in the right panel of Figure 1) show that the general level of satisfaction increases with time and manifests a decreasing heterogeneity among respondents. A remarkable step in rising the expressed satisfaction is noticeable between $S_i^{(3)}$ and $S_i^{(5)}$ when the time elapsed from the conclusion of university studies is long enough to express a more definite opinion with a reduced indecision.

## 4. SIGNIFICANT DRIVERS FOR JOB SATISFACTION

Since the satisfaction expressed 5 years after graduation implies a meditated and almost definitely oriented consideration about one's working conditions, in this section, the reference response $S_i^{(5)}$ will be the evaluation to be interpreted. Then, variable selection has been pursued to identify significant drivers to enter the logit specification of CUB regression model (1)-(2) for both uncertainty and feeling: *respondents'* characteristics (Geographical area, Gender); *job* typologies (Public, Fulltime); *University* curriculum (Age at degree, Mark); *degree-job matching* (Efficacy, Competence).

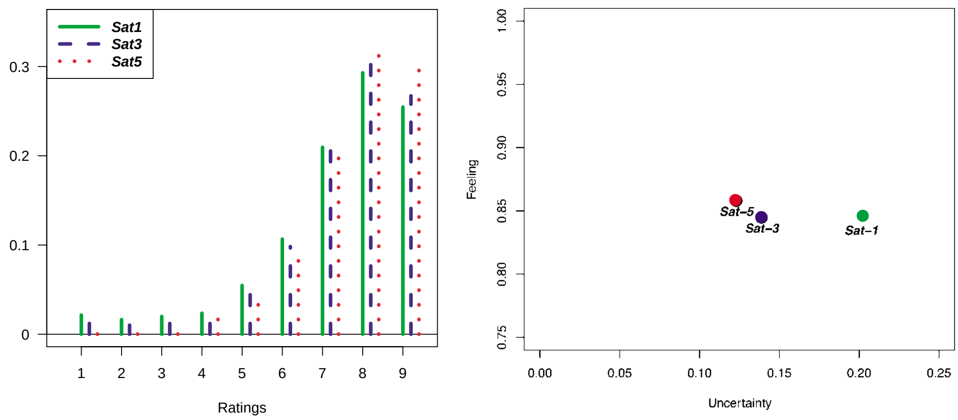


**Fig. 1: Job satisfaction at 1, 3 and 5 years after graduation: frequency distribu- tions (left) and CUB models representation (right)**

First of all, the selected methodology is applied to summarize any effect on job satisfaction responses by considering each covariate in turn; then, in the final subsection, explanatory covariates will be jointly considered for the estimation of a global model. The results here reported refer only to significant variables which induce a relevant increase in log-likelihood measures with respect to the benchmark, that is a CUB model without covariates.

Thus, CUB models have been estimated with respect to different clusters and visually represented in comparable subspaces of the unit square (to improve their readability). This perspective is by far more immediate for interpretation as compared to a list of numerical estimates since it summarizes all sufficient information, given the model specification.

## 4.1 RESPONDENTS' CHARACTERISTICS

Undoubtedly, gender and geographical area where people have achieved their degree encompass several aspects of both personal and socio-economic factors.

Left panel of Figure 2 shows CUB estimated models for job satisfaction at 5 years after graduation for men and women and depicts higher satisfaction for women, even showing their greater heterogeneity: this situation might be the result of different working conditions and expectations. Even if women are globally more satisfied, this evaluation may be more varied depending on personal circumstances as marital status, presence of children, age, etc.

Right panel of Figure 2 displays how the location of the university affects graduates' satisfaction $S_i^{(5)}$ . Estimated CUB models for different areas are sufficiently

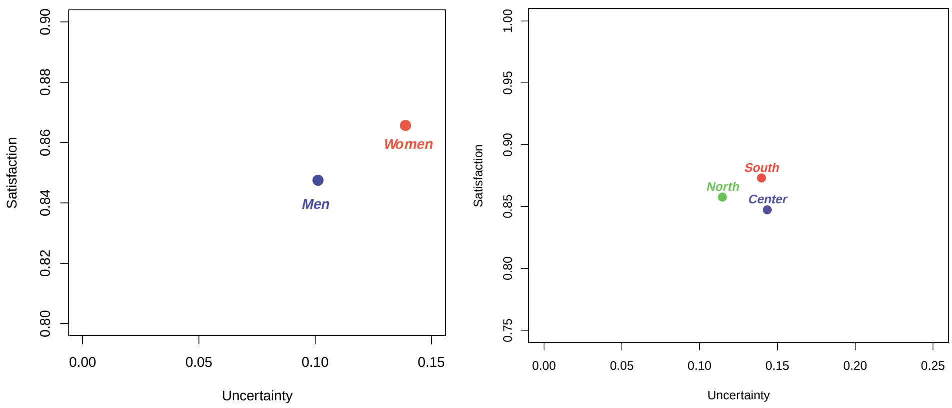


**Fig. 2: Effect of gender and University location on job satisfaction after 5 years**

homogeneous and graduates who studied in South Universities are characterized by a moderately greater satisfaction (for brevity, South denotes Italian Southern regions and islands).

## 4.2 JOB TYPOLOGIES

The 5 years job satisfaction has been considered with respect to sectors (public and private sectors) and intensity of the job (full-time and part-time). Since it may be suspected some interaction between stability (which should induce to prefer public sector) and intensity of the work (which depends on personal and family conditions), a joint model including both dichotomous covariates is considered.

A significant interaction whose effect is important for uncertainty turns out. The representation of the estimated model for all the combinations of job typology is depicted in Figure 3.

Whereas part-time workers manifest more uncertainty in the responses, public and private job typologies reverse the preferences when jointly considered with part-time and full-time jobs, respectively.

## 4.3 UNIVERSITY CURRICULUM

Curriculum is a prominent aspect to find a satisfactory job, and age at degree and final marks have been found to be significant to summarize these features. Age at degree is a synthesis of the regularity in studies but also of circumstances affecting the time devoted to tertiary education. Final mark may be an indicator of the level of competences and skills gained during the studies but it also depends on the

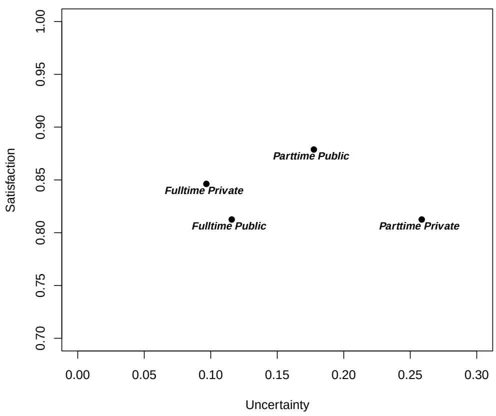


**Fig. 3: Effect of job typologies on job satisfaction after 5 years**

common mark averages in the chosen field of study.

Left panel of Figure 4 shows that satisfaction and uncertainty change with the age at degree with a significant parabolic effect. Thus, 5 years job satisfaction stays almost constant up to 35 years, then it systematically increases with age, with a moderate reduction in heterogeneity. Notice that, in the sample, about 1.7% of individuals is aged more than 50 years, with the 9th decile of the empirical distribution given by $D_9 = 36.79$ and the 95th percentile equal to 44.36.

Right panel of Figure 4 shows that job satisfaction at 5 years decreases with the value of the final marks which affect the level but not uncertainty. This circumstance has been confirmed in similar studies in Italy and stems from the disappointment of many young graduates who are compelled to accept a job which is not consistent with their competences and ambitions (Ferrante, 2014).

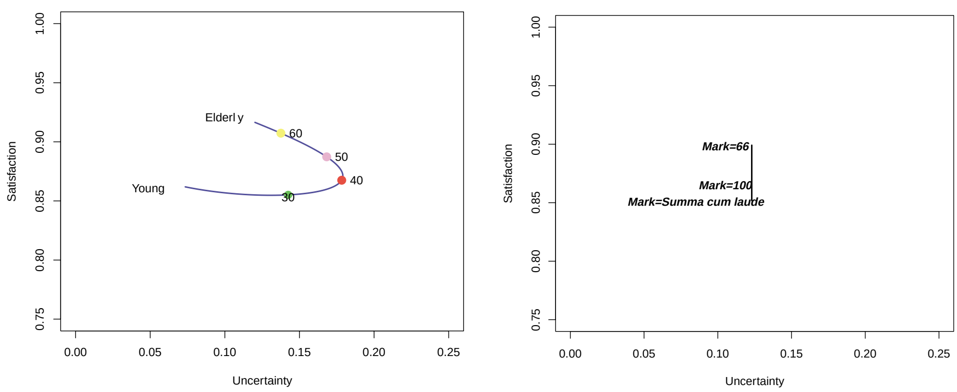


**Fig. 4: Effects of age at degree (left panel) and final mark on job satisfaction after 5 years**

A convergent but different interpretation is that university programs in some areas (as in social and human studies) yield modest occupational opportunities also for people with very high marks and this circumstance reduces the expressed job satisfaction. To check for this hypothesis in the dataset at hand, Humanities and Social Sciences (Law, Teaching, Humanities, Linguistic, Political and Social Sciences, Psychology) –which account for 41% of the sample– are separately examined. The average mark in this sample is greater but not significantly different from that of the other disciplines; however, whereas the expressed satisfaction at 1, 3, 5 years is virtually uncorrelated with those marks for different disciplines, the corresponding satisfaction expressed by graduates in Humanities and Social Sciences is significantly and negatively correlated in all the periods. Similar findings are in Gottard et al. (2006).

### 4.4 DEGREE EFFICACY

As already mentioned in Section 2, efficacy of the university studies with reference to current job of the interviewees is ranked on an ordinal scale with categories: "very effective" (=5), "effective" (=4), "fairly effective" (=3), "not very effective" (=2) and "ineffective" (=1). Each category is defined on the basis of the combination of two questions: use of the competences acquired at university; necessity of the academic qualification for the job activity (AlmaLaurea, 2015).

Then, further question related to the consistency of the university degree with one's job is asked, and responses are classified as "high" or "moderate/nothing".

Figure 5 depicts CUB models for job satisfaction 5 year after graduation with respect to efficacy and consistency with one's job, respectively. Thus, a high consideration of the efficacy is accompanied by resolute answers and very high satisfaction which decreases with the efficacy (Figure 5, left panel). Notice how this approach allows for the joint consideration of a drop in efficacy and a rise in responses heterogeneity.

Similarly, a high level of actual usage of the acquired competences generates very high satisfaction and low heterogeneity; the opposite occurs in case the competences are declared moderately useful or not useful at all (Figure 5, right panel).

### 4.5 FIELDS AND AREAS OF STUDIES

Italian degrees have been clustered according to the following 15 groups: *Agr* (Agricultural sciences and Veterinary medicine), *Arch* (Architecture), *Chem*

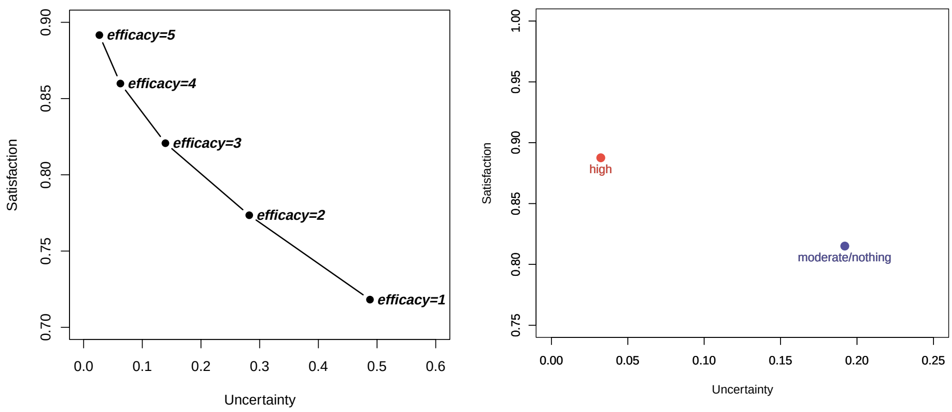


**Fig. 5: Job satisfaction with respect to efficacy (left) and consistency after 5 years (right)**

(Chemistry and Pharmacy), *EcoSt* (Economics and Statistics), *Gym* (Physical education), *GeoB* (Geology and Biology), *Law*, *Eng* (Engineering), *Teach* (Teaching/ Education sciences), *Hum* (Humanities), *Ling* (Linguistics), *Med* (Medicine), *PolSoc* (Political sciences and Sociology), *Psych* (Psychology), *Sci* (Sciences).

In this respect, job satisfaction after 5 years varies according to the fields of study as confirmed by the corresponding estimated CUB models whose main characteristics are reported in Table 1. Parameter estimates (asymptotic standard errors are in parentheses), sample size of each cluster, and a fitting measure are shown. All the estimates are significant and the dissimilarity index:

$$Diss = \frac{1}{2}\sum_{j=1}^{m}\left|\frac{n_j}{n} - Pr\left(R = j \mid \hat{\pi}, \hat{\xi}\right)\right|,$$

where $n_j$, $j = 1, 2, \ldots, m$ are the observed frequencies of the $j$-th category, implies a good fitting between empirical and estimated distributions. Such index quantifies the diversity of two distributions (defined on the same support) by considering their category-wise differences (the Duncan Segretation Index is an instance of its use), which is the complement to 1 of their overlapping (Simone, 2018): when used to compare observed frequencies and estimated probabilities, it gives the percentage of cases not fitted by the model.

Figure 6 shows the estimated models in the parameter space (full points refer to Humanities and Social Sciences fields). Thus, the graduates in Teaching/Education sciences and in Physical Education are those most satisfied (they are likely involved in educational activities, mostly in the public sector) whereas architects are comparatively more dissatisfied with their job. Notice that heterogeneity in response patterns is fairly higher for Humanities and Psychological degrees.

**Tab. 1: Estimated CUB models of job satisfaction at 5 years**

| Fields of studies | $1-\hat{\pi}$ | $1-\hat{\xi}$ | $n$ | *Diss* |
|---|---|---|---|---|
| *Agr* | 0.154 (*0.033*) | 0.857 (*0.009*) | 1074 | 0.088 |
| *Arch* | 0.135 (*0.019*) | 0.796 (*0.006*) | 1074 | 0.047 |
| *Chem* | 0.096 (*0.015*) | 0.867 (*0.005*) | 904 | 0.029 |
| *EcoSt* | 0.103 (*0.010*) | 0.843 (*0.003*) | 2351 | 0.017 |
| *Gym* | 0.164 (*0.034*) | 0.901 (*0.009*) | 262 | 0.105 |
| *GeoB* | 0.142 (*0.025*) | 0.849 (*0.007*) | 492 | 0.045 |
| *Law* | 0.147 (*0.026*) | 0.847 (*0.007*) | 508 | 0.039 |
| *Eng* | 0.070 (*0.008*) | 0.840 (*0.003*) | 3005 | 0.040 |
| *Teach* | 0.066 (*0.008*) | 0.935 (*0.002*) | 2107 | 0.069 |
| *Hum* | 0.223 (*0.022*) | 0.858 (*0.006*) | 985 | 0.076 |
| *Ling* | 0.147 (*0.021*) | 0.838 (*0.006*) | 707 | 0.050 |
| *Med* | 0.098 (*0.015*) | 0.865 (*0.005*) | 1123 | 0.051 |
| *PolSoc* | 0.148 (*0.013*) | 0.842 (*0.004*) | 1926 | 0.053 |
| *Psych* | 0.211 (*0.024*) | 0.825 (*0.007*) | 851 | 0.084 |
| *Sci* | 0.109 (*0.023*) | 0.858 (*0.007*) | 453 | 0.045 |

## 4.6 JOINT EFFECTS OF SELECTED COVARIATES

In order to rank the contribution given by each selected covariate (among those analysed in previous Sections) to explain job satisfaction expressed 5 years after degree, the log-likelihood functions estimated at maximum have been considered (here not reported for brevity). It turns out that self-assessed efficacy and degree-job matching are the most important drivers, followed by public and full-time employment, geographical area of studies, gender and, finally, degree marks and age at graduation. In addition, these drivers are also significant when all of them are inserted in a global CUB model:

$$\left\{ \begin{array}{lcl} logit\,(1-\hat{\pi}_i) & = & \underset{(0.157)}{1.406} - \underset{(0.040)}{0.879} Efficacy_i - \underset{(0.118)}{0.765} Fulltime_i\,; \\ logit\left(1-\hat{\xi}_i\right) & = & \underset{(0.190)}{1.681} - \underset{(0.022)}{0.079} Center_i + \underset{(0.025)}{0.068} South_i + \underset{(0.019)}{0.074} Gender_i \\ & & - \underset{(0.001)}{0.011} Ageatdegree_i + \underset{(0.016)}{0.150} Efficacy_i + \underset{(0.028)}{0.271} Fulltime_i \\ & & + \underset{(0.026)}{0.429} Public_i - \underset{(0.001)}{0.006} Mark_i + \underset{(0.032)}{0.286} Competence_i\,. \end{array} \right. \tag{3}$$

The log-likelihood of this model, computed at maximum, if compared with that of a model without covariates, largely increases (see Table 3 for reference), and the direction of the significant effects of the covariates on uncertainty and feeling seems quite consistent with the expected one. The circumstance that in model (3) the sign and the importance of each covariate are regularly confirmed legitimises the previous discussion on the marginal effects of single covariates.

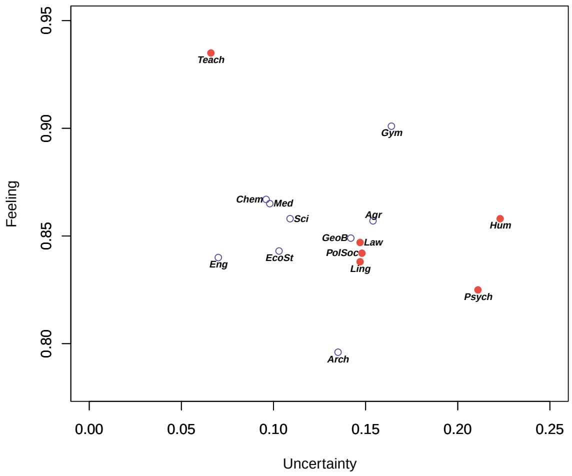


**Fig. 6: Estimated CUB models for different fields of studies**

## 5. EVOLUTION OF JOB SATISFACTION

Since dataset is a collection of several subjects' opinions over three time occasions, longitudinal methods should be exploited. In fact, subjective variability is a substantial issue of the responses as Table 2 would confirm: there is no sharp and definite direction in the observed changes from one period to the next one, although positive changes seem fairly dominant.

**Tab. 2: Frequencies of changes in job satisfaction between different times**

| Changes $1 \rightarrow 3$ years | Changes $3 \rightarrow 5$ years | | |
|---|---|---|---|
| | *Decrease* | *No change* | *Increase* |
| *Decrease* | 894 | 1463 | 3050 |
| *No change* | 1466 | 2918 | 1513 |
| *Increase* | 2565 | 2340 | 1276 |

In the same vein, *Corr* $(S_i^{(1)}, S_i^5)$ is positive but a regression line is unable to clarify what really occurs in the period from the first and the third evaluation for so many respondents. Figure 7 confirms an average increase between jittered responses, and a robust regression (using *lowess* method, as proposed by Cleveland (2016))

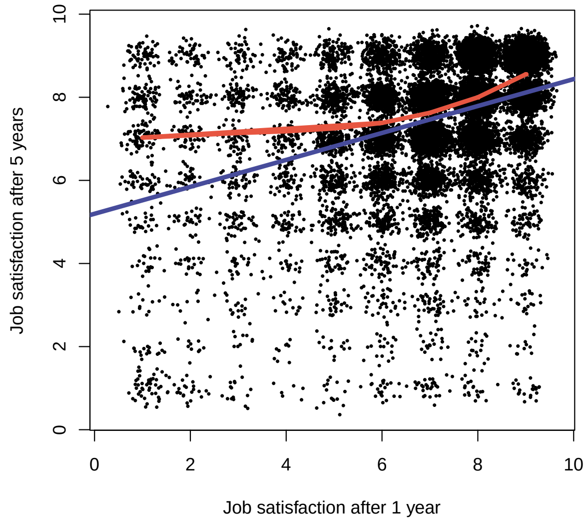


**Fig. 7: Job satisfaction after 5 versus 1 year: linear and lowess regression**

suggests more accurate conclusions. In fact, a low level of satisfaction does not change very much across the years, whereas a further increase is registered among those already highly satisfied in the first interview.

According to the latent growth curve modelling approach (Lu et al., 2011, among others), a study of individual latent trajectories as linear function of time could be of interest. For such random effect setup, we limit to mention that intercept effect is centered at 7.347 (with a standard deviation of 0.014), and the slope for time is centered at 0.167 (with a standard deviation of 0.008). Variances of random effects for intercept and slope are 1.966 and 0.366, resp. (with standard deviation of 0.047 and 0.021, resp.), whereas covariance between intercept and slope is estimated to be 0.307 (with a standard deviation of 0.025). This latent growth curve model has been estimated via the dedicated tools available within the lavaan package (Rosseel, 2012): similar results are obtained when fitting a linear mixed effect model with second-level clusters given by subjects trajectories over time. A devoted analysis for the dynamic setup according to the latent modelling approach is postponed to future research.

A different point of view, according to the modelling approach introduced in Section 3, is here performed in order to explain the main characteristics of the final responses as a function of the previous levels of the expressed satisfaction. In a sense, this approach is encompassed by transitional models; this kind of longitudinal models are debated with reference to problems caused by unobserved heterogeneity (initial condition problem: Aeberhardt and Davezies (2012); Bartolucci and Nigro

(2010); Skrondal and Rabe-Hesketh (2013)). CUB model specification, instead, does not include error component and inconsistency induced by correlation between explanatory covariates and errors cannot be accounted for. Indeed, the target is the estimation of the featuring parameters of the data generating process of the whole response distribution, with no specific focus on individual responses. Thus, the model we consider is not dynamic in the sense proper to panel data, but in the sense that we specify subjects' past evaluations as genuine information to explain the dependent variable.

The behaviour of job satisfaction across the waves may be considered by taking both heterogeneity/uncertainty and satisfaction level into account. At time $t$ = 5, the observed satisfactions $S_i^{(1)}$ and $S_i^{(3)}$ are well known and may be inserted in model (1) as explanatory covariates for both uncertainty and feeling, respectively. Then, the estimated CUB model is:

$$\begin{cases} logit\,(1-\hat{\pi}_i) & = \underset{(0.297)}{5.170} - \underset{(0.030)}{0.193}\, S_i^{(1)} - \underset{(0.040)}{0.928}\, S_i^{(3)}\,; \\ logit\left(1-\hat{\xi}_i\right) & = \underset{(0.068)}{-2.516} + \underset{(0.006)}{0.115}\, S_i^{(1)} + \underset{(0.009)}{0.455}\, S_i^{(3)}\,. \end{cases} \tag{4}$$

Estimates are obtained conditionally to observations at times $t$ = 1 and $t$ = 3. Parameters are largely significant and the estimated model attains a log-likelihood of $\ell(\hat{\beta},\hat{\gamma})$ = – 24201.82 to be compared with $\ell(\hat{\theta})$ = – 27699.22 of a CUB model without covariates.

Equations (4) show that both $S_i^{(1)}$ and $S_i^{(3)}$ exert a positive effect on the final satisfaction rate, quantitatively lower for $S_i^{(1)}$. The uncertainty/fuzziness surrounding the final evaluation, instead, decreases when including past expressed satisfaction, with a larger decrease induced by $S_i^{(3)}$ with respect to $S_i^{(1)}$. This is a consistent interpretation since low/high levels of satisfaction $S_i^{(1)}$ and $S_i^{(3)}$ induce high/low level of indecision in the responses $S_i^{(5)}$. Job satisfaction expressed 5 years after graduation is mainly affected by what interviewees declared 3 years (and also 1 year) post degree.

The implemented model allows for the prediction of the distributions of the responses at 5 years after degree for each $i$-th subject on the basis of the previous evaluations at time 1 and 3. As a matter of fact, the estimates of $\hat{\pi}_i$ and $\hat{\xi}_i$ are necessary and sufficient for the computation of $Pr\ (R_i = j)$, $j$ = 1, 2, … , $m$ according to (1).

Certainly, the issue of selection bias (Heckman, 1979; Wooldridge, 1995) is not directly encompassed by the dynamic model (4): in order to support such model against the issue of selection bias, we estimate it on sub-samples determined by geographical areas and (aggregated) fields of study. Figure 8 shows the corresponding

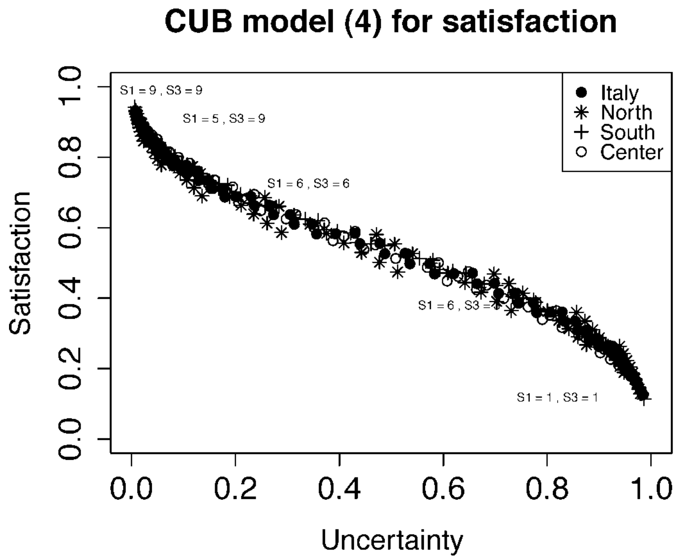


**Fig. 8: CUB model (4) for different geographical areas of Universities, given values of $S_1$ and $S_3$**

CUB parameters ($1 - \pi$, $1 - \xi$) for uncertainty and satisfaction in the parameter space, estimated for all Italian data and for sub-samples determined by aggregated geographical areas of the University, conditional to values of $S_1$ and $S_3$ (so that each point in the scatterplot corresponds to uncertainty and feeling at 5 years, given $S_1 = i$ and $S_3 = j$, for a given sample of data). Results show that there is no sensitive variation implied by alleged selection bias on the basis of the geographical areas of study. In this respect, a coefficient-wise comparison of model (6) below with model (4) and model (3) can be insightful.

A similar conclusion is attained when looking at Figure 9, showing regression parameters ($\beta_0$ ,$\beta_1$, $\beta_2$) and ($\gamma_0$ ,$\gamma_1$, $\gamma_2$) for the general model:

$$\begin{cases} logit\,(1-\pi_i) &= \beta_0 + \beta_1 S_i^{(1)} + \beta_2 S_i^{(3)}\,; \\ logit\,(1-\xi_i) &= \gamma_0 + \gamma_1 S_i^{(1)} + \gamma_2 S_i^{(3)}\,. \end{cases} \tag{5}$$

estimated for the sub-sample corresponding to the different fields of study, as listed in Table 1. As for aggregated geographical areas, evidence is given that a possible alleged selection bias due to the field of study does not affect the global conclusions established with model (4).

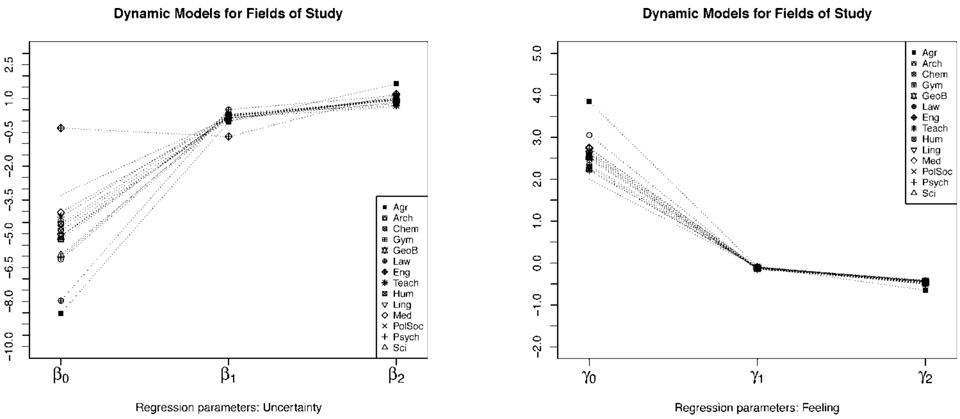


**Fig. 9: Regression parameters for model (4) estimated for each field of study**

## 6. A COMPREHENSIVE MODEL FOR JOB SATISFACTION

A more comprehensive model to explain $S_i^{(5)}$ would include past values of expressed job satisfaction as well contextual and subjects' covariates. Given the dataset and retaining only significant covariates in the global model, the estimated model turns out to be:

$$\left\{\begin{array}{lcl} logit\,(1-\hat{\pi}_i) & = & \underset{(0.360)}{5.859} - \underset{(0.032)}{0.134}\,S_i^{(1)} - \underset{(0.040)}{0.843}\,S_i^{(3)} - \underset{(0.053)}{0.449}\,Efficacy_i - \underset{(0.160)}{0.377}\,Fulltime_i\,; \\ logit\left(1-\hat{\xi}_i\right) & = & -\underset{(0.095)}{1.975} + \underset{(0.005)}{0.096}\,S_i^{(1)} + \underset{(0.009)}{0.387}\,S_i^{(3)} - \underset{(0.006)}{0.002}\,Center_i + \underset{(0.014)}{0.081}\,South_i \\ & & +\underset{(0.026)}{0.106}\,Gender_i - \underset{(0.160)}{0.377}\,Ageatdegree_i + \underset{(0.053)}{0.449}\,Efficacy_i \\ & & +\underset{(0.160)}{0.377}\,Fulltime_i + \underset{(0.025)}{0.227}\,Public_i - \underset{(0.001)}{0.003}\,Mark_i + \underset{(0.031)}{0.250}\,Competence_i\,. \end{array}\right. \tag{6}$$

Figure 8: CUB model (4) for different geographical areas of Universities, given values of $S_1$ and $S_3$.

This model attains higher log-likelihood than the previous ones, estimated parameters are significant and, most of all, the directions of association between covariates and dependent variables are consistent with those obtained in model (3).

Such a comprehensive model reasonably implies that uncertainty lowers for full-time workers and for people expressing high efficacy of their degree. In addition, model (6) explains satisfaction level as an increasing function of efficacy and competence which are higher for women, full-time workers and those in the public sector; on the contrary, satisfaction drops with age at degree and final mark. *Ceteris paribus*, the geographical effect seems to favour satisfaction of graduates of southern Universities with respect to northern ones.

Table 3 reports some indexes for comparing the different models fitted to $S_i^{(5)}$ : log-likelihood functions computed at maximum, BIC indexes and the number (*np*) of parameters involved in the models. Likelihood ratio tests (LRT) are referred to the first model since it is nested into models with covariates. Results show that the explanatory power of $S_i^{(1)}$ and $S_i^{(3)}$ is by far more important than that of a model which includes several subjective and contextual explanatory covariates. Thus, the expressed 5-year satisfaction seems mainly affected by previous subjective evaluations and subsequently by the selected variables, although this latter contribution should be seriously considered since it turns out to be significant.

**Tab. 3: Comparison of models of job satisfaction at 5 years**

| CUB *models* | *log-lik* | *BIC* | *LRT* | *np* | *MAPE* |
|---|---|---|---|---|---|
| Without covariates | −27699.22 | 55417.94 | − − − | 2 | 1.0531 |
| With covariates | −26162.92 | 52452.56 | 1536.31 | 15 | 1.0185 |
| With $S^{(1)}$ and $S^{(3)}$ | −24201.82 | 48462.14 | 3497.40 | 6 | 0.9008 |
| Model (6) | −23788.14 | 47742.03 | 3911.08 | 17 | 0.8921 |

These effects only partially interfere with covariates discussed in Section 4 since the inclusion of previous information in a comprehensive model does not modify the significance of those covariates and does not change the direction of effects, whereas it contributes to improve fitting.

Finally, a comparative performance of the fitted CUB models may be also checked in terms of predictive ability. Since ordinal models predict the whole distribution of the responses whereas observations concern single ratings, usually, a measure of discrepancy is obtained by averaging the absolute differences between the expressed satisfaction $r_i$ and the modal value $\hat{r}_i$ predicted by the estimated models. Thus, the Mean Absolute Prediction Error (MAPE) is defined as:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|r_i - \hat{r}_i\right| .$$

Table 3 lists such results for the estimated models. Again, the inclusion of significant covariates improve predictability of simpler models and, in this respect, lagged satisfaction adds a major contribution. For a fair evaluation of these measures, it should be noticed that a no-model prediction (that would predict the observed modal value of 8 for all the subjects) would be correct in 32% of cases.

Consistent results are obtained by using similar indexes for the predictive ability of CUB models, as those discussed by Piccolo and Simone (2019), among others.

## 7. CONCLUSIONS

This research is meant to ascertain the main drivers of job satisfaction expressed by a sample of employed Italian graduates, in the early years of their working life, as interviewed by AlmaLaurea Inter-University Consortium. The focus is on graduates that were employed at the time of all interviews run at 1, 3 and 5 years after graduation as MA. As a latent construct, job satisfaction is investigated using a specific class of mixture models for ordinal data able to interpret graduates' assessment as a blend of beliefs and inherent indecision, respectively. Visualization of these effects, also in relation to selected and significant covariates, is a positive result of the method.

The exploited models disclose the different contributions of the subjects' covariates on response patterns. In this regard, efficacy of studies and acquired competences are prominent drivers whose immediate effects are high satisfaction and small heterogeneity. Then, job characteristics, as public sector and full-time condition, are important to increase the expressed satisfaction. Noticeably, results change referring to geographical area (people graduated in southern Universities are more satisfied) and the response pattern is different also with respect to fields of study. These interesting results, as noted in Ferrante (2014) and AlmaLaurea (2015), need to be more deeply investigated in further research. Moreover, the main raise in satisfaction is registered from 3 to 5 years after graduation, as a consequence of the circumstance that in the early years people may also accept job that does not perfectly match with their skills and expectations.

Finally, the model-based approach has proven that, for the given dataset, past evaluations are the most important contributions to explain job satisfaction after 5 years from graduation, though subjects' and contexts' covariates add other significant and complementary information to this specification. In this respect, further research can be tailored to a more precise account of the initial condition problem and of the selection bias for the sample: these issues have not been addressed since the idea was to challenge the CUB framework to disentangle globally the drivers of job satisfaction but certainly they deserve more consideration. However, the findings here established seem to indicate that they might not be severely influential for the main conclusions here obtained.

The relevant result is a confirmation that job satisfaction is a blend of personal characterization, environmental stimulus and life course events where the choice of fields of study for an effective use and the acquired competences are really decisive.

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## REFERENCES


Aeberhardt, R. and Davezies, L. (2012). Practical guidelines for the estimation and inference of a dynamic logistic model with fixed-effects. In *Economic Letters*. 115: 300–304.

Agresti, A. (2010). *Analysis of Ordinal Categorical Data*. J.Wiley and Sons, Hoboken.

AlmaLaurea (2015). *XVII Rapporto sulla condizione occupazionale dei laureati*. AlmaLaurea, Bologna.

Attanasio, M. and Capursi, V. (2011). *Statistical methods for the evaluation of university systems*. Physica-Verlag, Berlin Heidelberg.

Bacci, S. and Gnaldi, M. (2015). A classification of university courses based on students' satisfaction: an application of a two-level mixture item response model. In *Quality & Quantity*. 49(3): 927–940.

Baltagi, B.H. (2008). *Econometric analysis of panel data,* 2*nd edition*. Wiley, Chichester, UK.

Bartolucci, F. and Nigro, V. (2010). A dynamic model for binary panel data with unobserved heterogeneity admitting a $\sqrt{n}$-consistent estimator. In *Econometrica*. 78: 719–733.

Bianchi, E.C. (2013). The bright side of bad times: The affective advantages of entering the workforce in a recession. In *Administrative Science Quarterly*. 58: 587–623.

Bird, S.M., Cox, D., Farewell, V.T., Goldstein, H., Holt, T. and Smith, P.C. (2005). Performance indicators: Good, bad, and ugly. In *Journal of the Royal Statistical Society A*. 168(1): 1–27.

Black, D.A. and Smith, J.A. (2006). Estimating the returns to college quality with multiple proxies for quality. In *Journal of Labor Economics*. 24: 701–728.

Boccuzzo, G., Fabbris, L. and Paccagnella, O. (2016). Job-major match and job satisfaction in italy. In *International Journal of Manpower*. 37(1): 135–156.

Boccuzzo, G. and Paggiaro, A. (2012). Facets of graduates' job satisfaction. In L. Fabbris, ed., *Indicators of higher education effectiveness*. McGraw-Hill Education, Milan: 133-136.

Budd, J.W. (2011). *The Thought of Work*. Cornell University Press, New York.

Bugamelli, M., Cannari, L., Lotti, F. and Magri, S. (2012). *Il gap innovativo del sistema produttivo italiano: radici e possibili rimedi, QEF*. Banca d'Italia, Roma.

Cagnone, S., Moustaki, I. and Vasdesk, V. (2009). Latent variable models for multivariate longitudinal ordinal responses. In *British Journal of Mathematical and Statistical Psychology*. 62: 401–415.

Cammelli, A. and Gasperoni, G. (2012). Higher education external effectiveness indicators with reference to italian universities. In L. Fabbris, ed., *Indicators of higher education effectiveness*. McGraw-Hill Education, Milan: 171–182.

Campostrini, S. and Gerzeli, S. (2007). Informative sources for the evaluation of the university education effectiveness in italy. In L. Fabbris, ed., *Effectiveness of University Education in Italy*. Physica-Verlag, Heidelberg New York: 1-9.

Capecchi, S. and Piccolo, D. (2016). Investigating the determinants of job satisfaction of italian graduates: a model-based approach. In *Journal of Applied Statistics*. 43(1): 169–179.

Cleveland, W.S. (2016). Robust locally weighted regression and smoothing scatterplots. In *Journal of the American Statistical Association*. 74(368): 829–836.

Corduas, M., Iannario, M. and Piccolo, D. (2009). A class of statistical models for evaluating services and performances. In P. Monari, M. Bini, D. Piccolo and L. Salmaso, eds., *Statistical Methods for the Evaluation of Educational Services and Quality of Products*. Physica–Verlag HD, Heidelberg: 99–117.

D'Elia, A. and Piccolo, D. (2005). A mixture model for preference data analysis. In *Computational Statistics & Data Analysis*. 49: 917–934.

Fabbris, L. (2012). Concepts, dimensions and indicators for measuring higher education effectiveness. In L. Fabbris, ed., *Indicators of higher education effectiveness*. McGraw-Hill Education, Milan: 1–20.

Fabbris, L. and Favaro, D. (2012). Graduates' human capital: an outcome in itself or an instrument for achieving outcomes? In L. Fabbris, ed., *Indicators of higher education effectiveness*. McGraw-Hill Education, Milan: 61–74.

Ferrante, F. (2014). Great expectations. The unintended consequences of educational choices. In *AlmaLaurea Inter–University Consortium Working Papers*. 67.

Folloni, G. and Vittadini, G. (2010). Human capital measurement: a survey. In *Journal of Economic Surveys*. 24(2): 248–279.

Frees, B.H. (2004). *Longitudinal and panel data*. Cambridge University Press, Cambridge.

Gottard, A., Grilli, L., and Rampichini, C. (2006). A multilevel chain graph model for the analysis of graduates' employments. In L. Fabbris, ed., *Effectiveness of University Education in Italy: Employability, Competences, Human Capital Indicators of higher education effectiveness*. Springer, Berlin: 169–182.

Green, F. and Mcintosh, S. (2007). Is there a genuine underutilisation of skills amongst the over-qualified? In *Applied Economics*. 39(4): 427–439.

Green, F. and Zhu, Y. (2010). Overqualification, job dissatisfaction, and increasing dispersion in the returns to graduate education. In *Oxford Economic Papers*. 62(4): 740–763.

Grilli, L. and Rampichini, C. (2009). Multilevel models for the evaluation of educational institutions: a review. In P. Monari, M. Bini, D. Piccolo, and L. Salmaso, eds., *Statistical Methods for the Evaluation of Educational Services and Quality of Products*. Physica–Verlag HD, Heidelberg: 61–80.

Heckman, J.J. (1979). Sample selection bias as a specification error. In *Econometrica*. 47: 153–161.

Hsiao, C. (2003). *Analysis of panel data, 2nd edition*. Cambridge University Press, Cambridge.

Iammarino, S. and Marinelli, E. (2011). Is the grass greener on the other side of the fence? Graduate mobility and job satisfaction in Italy. In *Environment and Planning*. 43: 2761–2777.

Iannario, M., Piccolo, D. and Simone, R. (2018). CUB: A class of mixture models for ordinal data. In *R package version 1.1.3. http://CRAN.Rproject.org/package=CUB*.

Lockheed, M.E. and Hanushek, E. (1994). *Concepts of educational efficiency and effectiveness*. Human resources development and operations policy working papers. no. HRO 24. Washington, DC: World Bank. http://documents.worldbank.org/curated/en/727651468739517517/Conceptsof-educational-efficiency-and-effectiveness. Last access: 30/09/2017.

Lu, T., Poon, W. and Tsang, Y. (2011). Latent growth curve modelling for longitudinal responses with applications. In *Computational Statistics and Data Analysis*. 55: 1488–1497.

Martini, M.C. and Fabbris, L. (2017). Beyond employment rate: A multidimensional indicator of higher education effectiveness. In *Social Indicators Research*. 130: 351–370.

Muñoz de Bustillo, R., Fernández-Macías, E., Antòn, J. and Fernando, E. (2011). *Measuring More Than Money - The Social Economics of Job Quality*. Edward Elgar, Cheltenham.

OECD (2012). *Better Skills, Better Jobs, Better Lives: A Strategic Approach to Skills Policies*. OECD Publishing, Paris.

OECD (2018). *Education at a glance 2018. OECD Indicators*. OECD Publishing, Paris.

Oshagbemi, T. (2003). Personal correlates of job satisfaction: empirical evidence from UK universities. In *International Journal of Social Economics*. 30(12): 1210–1232.

Piccolo, D. (2003). On the moments of a mixture of Uniform and shifted Binomial random variables. In *Quaderni di Statistica*. 5: 85–104.

Piccolo, D. (2006). Observed information matrix for MUB models. In *Quaderni di Statistica*. 8: 33–78.

Piccolo, D. and Simone, R. (2019). The class of CUB models: Statistical foundations, inferential issues and empirical evidence (with discussion). In *Statistical Methods and Applications*. 28(3): 389–435.

Piccolo, D., Simone, R. and Iannario, M. (2019). Cumulative and CUB models for rating data: A comparative analysis. In *International Statistical Review*. 87(2): 207–236.

Ricci, A. (2011). *Istruzione, formazione e mercato del lavoro: i rendimenti del capitale umano in Italia*. ISFOL, Roma.

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. In *Journal of Statistical Software*, 48 (2): 1–36.

Schomburg, H. and Teichler, U. (2006). *Higher education and graduate employment in Europe: Results of graduate surveys from twelve countries*. Kluwer, Dordrecht.

Simone, R. (2018). A test for variable importance. In *Book of Short Papers SIS 2018*. A. Abbruzzo, E. Brentari, M. Chiodi and D. Piacentino (eds). Pearson Publisher, Milano: 1–6.

Skrondal, A. and Rabe-Hesketh, S. (2013). Handling initial conditions and endogeneous covariates in dynamic/transition models for binary data with unobserved heterogeneity. In *Journal of the Royal Statistical Society: Series C (Applied Statistics)*. 63: 211–237.

Switek, M. (2013). *Explaining well-being over the life cycle: A look at life transitions during young adulthood*. IZA Discussion Paper, No. 7877.

Tutz, G. (2012). *Regression for Categorical Data*. Cambridge University Press, Cambridge.

Verhofstadt, E., De Witte, H. and Omey, E. (2007). Higher educated workers: better jobs but less satisfied? In *International Journal of Manpower*. 28(2): 135–151.

Vila, L.E., Garcia-Aracil, A. and Mora, J. (2007). The distribution of job satisfaction among young european graduates: Does the choice of study field matter? In *The Journal of Higher Education*. 78(1): 97–118.

Visco, I. (2014). *Investire in conoscenza*. Il Mulino, Bologna.

Weiss, H.M. (2002). Deconstructing job satisfaction: Separating evaluations, beliefs, and affective experiences. In *Human Resource Management Review*. 12: 173–194.

Wooldridge, I. (1995). Selection corrections for panel data models under conditional meand independence assumptions. In *Journal of Econometrics*. 68: 115–132.