Measurement of University External Effectiveness Based on the Use of the Acquired Skills

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Summary. In this paper, we analyse the skills used at work, 18 to 30 months from the completion of studies, by the students who graduated at the University of Florence in the year 2000. The aim is pursued by detecting the determinants of the phenomenon with particular attention to the possible differences between study programmes. We performed two analyses: in the first, we identified homogeneous groups of degree programmes and applied a proportional odds (logistic) model for each group and a partial proportional odds model for the whole university. The second analysis was an ordered logistic model with random intercept having two levels of aggregation with the degree types as second-level units.
Keywords: University effectiveness; Skills; Ordered logistic regression, Proportional odds models; Partial proportional odds models; Multilevel models; Cluster analysis.

1. The evaluation of external effectiveness

One of the ways of assessing the quality of the education offered by a university is to evaluate its performance in terms of internal and external efficiency and effectiveness. External effectiveness is the 'capacity' of a university programme to satisfy labour market needs as indicated by the first-employment rate (Chiandotto & Bacci, 2004), the length of time lapse between graduation and employment, the actual usefulness of the qualifications for the work undertaken, the degree to which graduates use at work the skills they have acquired at university, and so on.

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[1] The idea, the structure and the setting out of the contribution are due to both the authors; the data processing and the estimate of the models have been done by S. Bacci.

In this research, we focused on the use of skills that graduates achieved at university, with particular reference to the capacity of study programmes of creating the competences required by the labour market. For this purpose, after an appropriate aggregation of study programmes, we estimated a logistic regression model for every aggregation of graduates as well as for the entire contingent of the employed graduates. In this latter case, the groups of programmes were given the role of explicative variable. Thereafter, the results obtained were compared with those from the application of a multilevel logistic regression model on the same set of data; in this application, the programmes represented second-level units.

In Section 2, we discuss the phenomenon under study and its possible interactions with both the individual variables and different types of jobs. In Section 3, we analyse the resulting groups, while in Sections 4 and 5 we discuss the predictions and the results of the fitting of a regression model according to study programme and for the whole Florence University, for finding the net effect of the determinants of the achieved skill use. In Sections 6 and 7, we comment on the estimates obtained with a multilevel regression model. At the end, conclusions about the advantages and drawbacks of using a multilevel model for hierarchic models are drawn.

2. The skill use of the University of Florence graduates

In the year 2000, 5245 students graduated from Florence University. Out of these, 4846 had a Master and 399 a Bachelor degree. Of the 3856 graduates we interviewed, 2882 (approximately 75%) resulted to be working at the time of the interview: 1867 (64.8%) were using intensively the skills they had acquired at university, 730 (25.3%) were using it to a fair extent, while the other 285 (9.9%) did not use it at all.

The response distributions are far from being homogeneous with either the study programme[2] or the faculty (Table 1). For instance, the graduates in the Humanities who said their occupation entailed considerable use of the skills acquired at university went from 40.0% (Philosophy) to 65.0% (Modern foreign language and literature), while the graduates in Science ranged from 45.8% (Natural science) to 81.3% (Physics).

A comparison between the faculties revealed great differences. Taking into account the "considerable use of the skills", there was an 86.7% of graduates from Medicine and an 81.5% of those from Pharmacy.

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[2] Because of the small numbers of graduates, Political economics has been merged with Economics, Tropical and subtropical agriculture and relative Sciences to Agronomy; moreover, the two courses in Foreign language and literature under Letters and Philosophy and Formation Science have been considered as a single study programme.

Table 1. Use of the university skills at work, by study programme and faculty

Faculty/programme	**High**	***%***	**Fair**	***%***	**Not at all**	***%***	***Graduates***
AGRICULTURE	**44**	***60.3***	**17**	***23.3***	**12**	***16.4***	***73***
Agronomy	11	*55.0*	7	*35.0*	2	*10.0*	*20*
Forestry	17	*63.0*	6	*22.2*	4	*14.8*	*27*
Forestry and environmental st.	11	*61.1*	3	*16.7*	4	*22.2*	*18*
Scientific and technical agronomy	5	*62.5*	1	*12.5*	2	*25.0*	*8*
ARCHITECTURE	**378**	***68.0***	**155**	***27.9***	**23**	***4.1***	***556***
Architecture	378	*68.0*	155	*27.9*	23	*4.1*	*556*
ECONOMICS	**361**	***72.6***	**121**	***24.3***	**15**	***3.0***	***497***
Business economics	15	*83.3*	3	*16.7*	-	-	*18*
Economics	323	*72.3*	111	*24.8*	13	*2.9*	*447*
Actuarial and statistical science	17	*70.8*	5	*20.8*	2	*8.3*	*24*
Statistical and economic science	6	*75.0*	2	*25.0*	-	-	*8*
PHARMACY	**53**	***81.5***	**10**	***15.4***	**2**	***3.1***	***65***
Chemistry and pharmac. techn.	25	*89.3*	3	*10.7*	-	-	*28*
Pharmacy	28	*75.7*	7	*18.9*	2	*5.4*	*37*
LAW	**120**	***63.2***	**43**	***22.6***	**27**	***14.2***	***190***
Law	120	*63.2*	43	*22.6*	27	*14.2*	*190*
ENGINEERING	**224**	***71.8***	**72**	***23.1***	**16**	***5.1***	***312***
Civil engineering	68	*81.9*	15	*18.1*	-	-	*83*
Electronic engineering	57	*62.0*	27	*29.3*	8	*8.7*	*92*
Mechanical engineering	48	*69.6*	17	*24.6*	4	*5.8*	*69*
Computer engineering	11	*64.7*	6	*35.3*	-	-	*17*
Environmental engineering	31	*81.6*	3	*7.9*	4	*10.5*	*38*
Telecommunication engineering	9	*69.2*	4	*30.8*	-	-	*13*
LETTERS and PHILOSOPHY	**186**	***53.6***	**96**	***27.7***	**65**	***18.7***	***347***
Philosophy	14	*40.0*	11	*31.4*	10	*28.6*	*35*
Letters	97	*52.4*	48	*25.9*	40	*21.6*	*185*
Foreign language and literature	38	*55.1*	24	*34.8*	7	*10.1*	*69*
Modern foreign lang., literature	26	*65.0*	9	*22.5*	5	*12.5*	*40*
History	11	*61.1*	4	*22.2*	3	*16.7*	*18*
MEDICINE	**65**	***86.7***	**9**	***12.0***	**1**	***1.3***	***75***
Medicine and surgery	39	*84.8*	6	*13.0*	1	*2.2*	*46*
Dentistry and dental prosthesis	26	*89.7*	3	*10.3*	-	-	*29*
FORMATION SCIENCE	**208**	***67.3***	**64**	***20.7***	**37**	***12.0***	***309***
Foreign language and literature	10	*62.5*	2	*12.5*	4	*25.0*	*16*
European foreign lang. and liter.	8	*61.5*	3	*23.1*	2	*15.4*	*13*
Humanities	14	*60.9*	4	*17.4*	5	*21.7*	*23*
Pedagogy	23	*57.5*	11	*27.5*	6	*15.0*	*40*
Psychology	28	*62.2*	12	*26.7*	5	*11.1*	*45*
Educational science	125	*72.7*	32	*18.6*	15	*8.7*	*172*
POLITICAL SCIENCE	**85**	***36.0***	**100**	***42.4***	**51**	***21.6***	***236***
Political science	85	*36.0*	100	*42.4*	51	*21.6*	*236*

Faculty/programme	**High**	*%*	**Fair**	*%*	**Not at all**	*%*	***Graduates***
SCIENCE	**143**	***64.4***	**43**	***19.4***	**36**	***16.2***	***222***
Chemistry	27	*69.2*	6	*15.4*	6	*15.4*	*39*
Physics	13	*81.3*	2	*12.5*	1	*6.3*	*16*
Mathematics	12	*48.0*	10	*40.0*	3	*12.0*	*25*
Biology	48	*64.9*	12	*16.2*	14	*18.9*	*74*
Information science	7	*58.3*	5	*41.7*	-	-	*12*
Geology	25	*78.1*	4	*12.5*	3	*9.4*	*32*
Natural science	11	*45.8*	4	*16.7*	9	*37.5*	*24*
Total	**1,867**	***64.8***	**730**	***25.3***	**285**	***9.9***	***2,882***

On the other hand, the majority of those who said that they were not able to make any use of the acquired skills had graduated from Political Science (21.6%), Letters and Philosophy (18.7%), Agriculture (16.4%) and Sciences (16.2%). Overall, the qualifications that corresponded to the widest use of skills are the 'technical' ones, while the general, non-technical, qualifications (such as Political Science) encountered greater difficulties in job searching.

The high levels of Cramer's V and Chi-square statistics (0.236 and 299.329, respectively; $p<0.0001$) point out a significant difference between the type of studies undertaken and use of the skills: that is why we examined the influence exerted by the specific study programmes.

There are factors other than the type of degree that can influence the use of the acquired skills at work (Chiandotto *et al.*, 2004). The highest percentages of graduates who use the acquired skills are employed in small firms, have taken at least one post-graduate programme and either have a managerial position or are self-employed.

Moreover, the skill use is positively correlated with both job satisfaction and the perceived usefulness of the qualifications for the work duties.

3. Response variable and cluster analysis

We applied an ordinal logistic regression model. The response variable was *the use at work of the skills acquired at university* on a three level scale: high (Y=1), fair (Y=2), not at all (Y=3).

Since our aim was to assess the effect exerted by the study programme on the response variable, the programmes have been aggregated in order to estimate a model for every group detected. Another model was estimated for the entire contingent of graduates with the programmes as an esplicative variable[3].

[3] From a theoretic point of view, these analyses could have been performed by study programme rather than groups of programmes. We grouped the data because of the small number of graduates in several courses and because of the large number of programmes.

Due to the differences between study programmes within the same faculty (Table 1), we grouped them with a cluster analysis (Chiandotto, 1978). We adopted the hierarchic grouping method based on minimum variance (Ward's approach)[4]. The variables were selected according to their explicative capacity between programmes[5]: median age at graduation, median final marks on degree, median finals marks at secondary school, % of males, % of graduates who attended an internship to complete the studies, % of graduates who had work experience during university studies, and % of graduates coming from classical or scientific high schools.

The cluster analysis formed four groups of study programmes[6] (Table 2): Group 1 contains mainly programmes of the humanities and formative science and theoretical programmes (Biology and Natural science); Groups 2 and 3 include programmes of a technical nature (Group 2 refers roughly to economics and engineering while Group 3 to health fields); Group 4 corresponds almost entirely to Agriculture.

From the analysis of the aggregation variables, profiles that are more specific emerged (Table 3). In the study programmes of Group 1 there is a prevalence of female graduates (62.4%), who come from classical or scientific high schools (76.6%), had generally low final marks at secondary school (21.7% had marks ranging from 36/60 to 40/60) and took quite a long time to complete their university studies (12.3% were over 6 years over the prescribed time and 26.2% graduated after 30 years).

Group 2 was the only one with a prevalence of males (55.9%) and with the highest percentage of technical school diploma-holders (40.0%). The high school final marks of these graduates were high (25.5% achieved their secondary school diploma with at least 55 out of 60), whereas their graduation marks were the lowest in the university (54.8% graduated with less than 100/110 and only 14.2% received a 110/110 degree cum laude[7]) and the time taken to complete their studies was longer (25.6% took more than twice the programme duration).

The majority of graduates in Group 3 came from classical or scientific high schools (82.4%), with high final marks at school (38.6% had marks over 55/60) and with less previous work experience than the other groups (only

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4 Ward's method was chosen because the other grouping methods (complete link, median and centroid methods) gave unsatisfactory results in terms of distribution of the study programmes among groups: there was a tendency to form a principal group containing programmes heterogeneous with one another and of several small groups.

5 The grouping variables have been standardized (zero mean and unit variance) because of different units of measurement.

6 We partitioned into four groups because a finer aggregation would have generated problems in the maximization of the likelihood function for the estimation of the model, especially for groups containing very few individuals.

7 In the other three groups, the same frequency did not exceed 21.6% (Group 3), in the first case and at least 34.6% (Group 3) in the second case.

45.1% vs. 70-80%). However, 34.6% of them attended an internship in order to complete their studies (compared with the 7-8% of those in groups 1 and 2). The graduates in this group took the shortest length of time to finish their studies: almost 25% of them graduated within the established time.

Group 4 showed a prevalence of females (69.8%) and subjects from technical schools (38.8%), with low final marks at school (26.4% had marks under 41/60). However, 93.8% of them had attended an internship and 58.9% graduated within less than one and a half times the normal time.

Table 2. Composition of the study programme groups

GROUP 1	**GROUP 2**	**GROUP 3**	**GROUP 4**
Architecture	Business economics	Chemistry	Agronomy
Philosophy	Economics	Chem.+pharm. techn.	Forestry
Letters	Law	Pharmacy	Educational science
Foreign language & lit.	Civil engineering	Physics	Scient. techn. agronomy
Modern foreign lang. lit.	Electronic engineer.	Medicine and surgery	Forestry and environ. st.
European foreign lang. l.	Computer engineer.	Dentistry dental pros.	
Humanities	Mechanical engin.	Environmental engin.	
Pedagogy	Mathematics	Telecommunic. eng.	
Psychology	Information science		
Biology	Geology		
Natural science	Political science		
Actuarial and statistics.			
Statistics and economics			
History			

Table 3. Profiles of the study programme groups (percentage values)

	GROUP 1	**GROUP 2**	**GROUP 3**	**GROUP 4**
Female	62.4	44.1	51.0	69.8
High school: *Lyceum*	76.6	60.0	82.4	61.2
Diploma mark >55/60	19.0	25.5	38.6	13.2
Graduates in legal time	6.2	2.3	24.2	13.2
Degree mark <100/110	11.0	54.8	21.6	8.5
Work during university	74.0	73.2	45.1	83.0
Internship	7.1	8.2	34.6	93.8
Graduates (n)	*1170*	*1221*	*246*	*245*

4. Independent variables

The models for investigating the use of skills were estimated on 2882 newly graduated subjects in the year 2000 at Florence University who were employed at the time of interview. The explanatory variables were selected according to the descriptive analyses (see Section 2) and to our prior knowledge.

The following covariates were included at least in one of the initial steps:

Quantitative explicative variables

1. *Graduation marks* (*gradmark*). It is the mark at graduation that ranges from 66 to 113 over 110 (113 corresponds to 110 cum laude). Since the variables referring to the graduation mark and to the mean of the marks achieved in the examinations are strongly correlated (r=0.84), only the first variable was included in the model to avoid multicollinearity.
2. *Age at graduation* (*agegrad*), ranging from 21.9 years to 67.6 years.
3. *Final secondary school marks* (*finmark*), ranging from 36/60 to 60/60.
4. *Number of hours worked per week* (*num_hrs*) ranging from 2 to 90; the highest frequency corresponded to 30, 36, 40, 45 and 50 hours per week.

Qualitative explicative variables

5. *Gender* (*gend*): it is a binary variable with categories 'female' (*female*) and a 'male' (*male*). Since the female graduates were 56.4%, 'female' was the reference category.
6. *Work experience during studies* (*work1*): this is a binary variable (*work1_no* if the graduate did not have work experience during his/her studies and *work1_yes* otherwise). Even though the majority of graduates had had experience of work during their studies, the 'no' category was chosen as reference in order to directly interpret the estimated coefficient.
7. *Attendance of an internship or training programme for completion of the studies* (*stage*). It is a binary variable with categories 'no-internship' (*stage_no*) and an 'internship done' (*stage_yes*). More than 83% of the graduates did not attend an internship.
8. *Type of high school diploma* (*typdip*). Its categories are: 'classical' (*classics*), 'scientific' (*scientific*), 'technical' (*technical*), 'other' (*othdip*). The 'scientific' category was the reference.
9. *Social class background* (*p_socgen*). Its categories are: 'upper middle class' (*upper* – adopted as reference), 'white-collar middle class' (*white-collar*), 'lower middle class' (*low_mid*), 'working class' (*working*).
10. *Knowledge of English* (*lang1_gb*). Its categories are: 'non/poor' (*engl_poor*), 'sufficient' (*engl_suff*), 'good' (*engl_good*), 'excellent' (*engl_excel*). The majority of graduates had a good knowledge of English.

11. *Knowledge of word processors* (*info3_wp*). Its categories are the same as those for *langl_gb*; the most frequent was that referring to a good knowledge of word processors (*wp_good*).
12. *Geographical area of work site* (*site_work*). Its categories are 'Florence and Province', 'North and abroad', 'Centre', 'South'; the 'Florence and Province' category was taken as reference. The work site was considered more interesting for analytical purposes than that of the area of residence of graduates, since the latter does not always coincide with the work site.
13. *Occupation at graduation* (*occgrad*). Its categories are: already working at the time of graduation and still the same work, working at the time of graduation and changed work, not working at the time of graduation (this last was taken as reference).
14. *Type of work* (*typ_work*) with categories, with categories: 'employee' (reference mode – *employ_work*) and self-employed' (*self_work*).
15. *Type of contract* (*typ_contr*) with categories 'tenure employment' (mode used as reference) from 'precarious'; this latter is comprehensive of all types of contracts limited in time (such as contracts for collaboration, training, etc.).
16. *Economical field of business* (*econbus*): with categories 'public' (*public*) and 'private' (*private*); the latter was taken as reference.
17. *Professional position of the graduate* (*prof_pos*): the original categories were 'manager', 'employee', 'free-lance', 'self-employed worker' and 'other'. When the model was being estimated, this variable turned out to be somewhat significant though with just some categories, so dichotomization was resorted to by distinguishing employees and workers on one side (mode taken as reference – *employ/worker*) and managers, free-lancers and self-employed workers (*man/free*) on the other, in order to separate 'lower' from 'higher' professional positions.
18. *Post-graduate qualification accomplished* (*post_grad*): it is a binary variable aimed at assessing the effect of post-graduate studies on the quality of job.
19. *Size of the firm*[8] (*size_firm*): a distinction was made between 'small/medium firm' (*small_firm* – max. 50 employees) and 'large firm' (*large_firm* – over 50 employees)
20. *Qualification necessity* (*necess*): a distinction was made between the qualifications required by law (*qualif_law*), qualification actually useful (even if not compulsory by law – *qualif_useful*) and qualification useless for the type of work performed (*qualify_useless*). The 'qualification required by law' was adopted for reference.
21. *Satisfaction in work performed* (*satisf*) with categories: 'great/very great' (*very_satisf*), 'sufficient' (*sufficient_satisfy*), 'little or none at all'

[8] Note that the term 'firm' is intended as workplace in general, and defines both private companies and public entities.

(*little_statisf*) and refers to job satisfaction. Most graduates were very satisfied with their work.

22. *Search for new work* (*search_work*) for which a distinction was made between those already employed but on the lookout for a new position and those already working but not in search of a new position.

5. Proportional odds logistic model and partial proportional odds logistic model

The nature of the variable response (ordinal polytomous with three categories) and the results of the *score* test for evaluating the hypothesis of *proportional odds* suggested the use of an ordinal logistic model with proportional odds for each one of the four groups of degree programmes, with the following general structure expressed in logit terms (McCullagh & Nelder, 1989: chapter 5)

$$\begin{cases} \text{logit}(P_{1i}) = \log\left(\dfrac{P_{1i}}{1-P_{1i}}\right) = \log\left(\dfrac{P_{1i}}{P_{23i}}\right) = \alpha_1 + \sum_{j=1}^{h} \beta_j \cdot x_{ji} \\ \text{logit}(P_{12i}) = \log\left(\dfrac{P_{12i}}{1-P_{12i}}\right) = \log\left(\dfrac{P_{12i}}{P_{3i}}\right) = \alpha_2 + \sum_{j=1}^{h} \beta_j \cdot x_{ji} \end{cases}$$

where: i indicates a generic graduate, $Pr(Y=1)=P_1$, $Pr(Y=2)=P_2$, $Pr(Y=3)=P_3$, $P_1+P_2=P_{12}$, $P_2+P_3=P_{23}$, α_1 and α_2 the intercepts of the two logit models, x_j is the j^{th} explicative variable and β_j is the corresponding regression coefficient; in this case, the covariate number h is equal to *22*.

A logistic model for ordinal data is a set of logistic models for binary data as the number of categories of the Y response variable minus one. In the same way as for the dichotomous case and in the presumption of proportional *odds,* the β_j coefficient of regression can be interpreted as the increase (if positive), or as the decrease (if negative), that the *logits* undergo with a unit increase of the x_j predictor. With a 3-mode Y, e^{β_j} indicates both the *odds* of P_1 compared to P_{23} and the *odds* of P_{12} compared to P_3.

We estimated the four models with the PROC LOGISTIC of SAS software, using the Fisher-scoring maximization algorithm; the explicative variables and any quadratic or interaction effect were selected with the *forward* procedure[9]. To assess the goodness of fit, we adopted the likelihood and score tests and computed Pearson's statistics and deviance, and R-square[10]. The significance

[9] We applied also stepwise and backward selection procedures. In the case of Groups 1, 2 and 4 they produced identical results. Vice versa, in the model referring to Group 3 there were problems of fitting and convergence of the maximization algorithm.

[10] For non-linear models, the R^2 very seldom reaches high values; hence, a 20-25% quota of explained variance may be satisfactory.

of the coefficients was evaluated with Wald's tests[11].

Table 4 shows the list of selected covariates, the estimates of the intercepts and coefficients of regression; together with the relative standard errors and the results of Wald's test (significance was 10%). The reference category is labelled '0'.

The last column shows the odds ratio, i.e. the variation of P_1 with respect to P_{23} or, similarly, of P_{12} with respect to P_3, with a unit increase of an explicative variable.

Table 4. Proportional odds ordered logistic models, for every group

Effect	*Reference*	*Estimate*	*Standard Error*	*Value t*	*p-value*	*Odds ratio*
Group 1 (R^2=0,27)						
Intercept 1	-	1.9775	0.1885	110.0778	<.0001	-
Intercept 2	-	3.8092	0.2607	213.5712	<.0001	-
qualif_useful	*qualif_law*	-0.8117	0.2261	12.8918	0.0003	0.444
qualif_useless	*qualif_law*	-3.3951	0.3536	92.1649	<.0001	0.034
search_work_yes	*search_work_no*	-0.6415	0.2512	6.5232	0.0106	0.526
sufficient_satisfy	*very_satisfy*	-0.6897	0.2279	9.1625	0.0025	0.502
little_satisfy	*very_satisfy*	-1.4907	0.3642	16.7531	<.0001	0.225
Group 2 (R^2=0,22)						
Intercept 1	-	-2.4672	1.2882	3.6680	0.0555	-
Intercept 2	-	-0.2560	1.2856	0.0397	0.8422	-
post_grad_no	*post_grad_yes*	-0.3506	0.1675	4.3810	0.0363	0.704
man/free	*employ/worker*	0.4196	0.2061	4.1440	0.0418	1.521
large_firm	*small_firm*	-0.4888	0.1797	7.3975	0.0065	0.613
qualif_useful	*qualif_law*	-1.1002	0.1932	32.4162	<.0001	0.333
qualif_useless	*qualif_law*	-3.0929	0.3504	77.9196	<.0001	0.045
sufficient_satisfy	*very_satisfy*	-0.6967	0.1831	14.4867	0.0001	0.498
little_satisfy	*very_satisfy*	-1.3932	0.3213	18.8010	<.0001	0.248
gradmark	-	0.0463	0.0124	13.8852	0.0002	1.047
Group 3 (R^2=0,20)						
Intercept 1	-	8.3295	2.4155	11.8907	0.0006	-
Intercept 2	-	9.8271	2.4746	15.7702	<.0001	-
post_grad_no	*post_grad_yes*	-1.0962	0.5044	4.7233	0.0298	0.334
self_work	*employ_work*	2.7989	1.2444	5.0594	0.0245	16.427
little_satisfy	*very_satisfy*	-1.2445	0.5154	5.8305	0.0158	0.288
public	*private*	1.8586	0.5388	11.8975	0.0006	6.415
agegrad		-0.2624	0.0896	8.5806	0.0034	0.769

[11] The former one was applied to assess the overall significance of each discrete polytomous covariate; the latter was used for evaluating the significance of the individual estimated coefficients of regression.

Effect	*Reference*	*Estimate*	*Standard Error*	*Value t*	*p-value*	*Odds ratio*
Group 4 (R^2=0,26)						
Intercept 1	-	2.2181	0.5576	15.8256	<.0001	-
Intercept 2	-	3.3970	0.6229	29.7390	<.0001	-
post_grad_no	*post_grad_yes*	-1.3308	0.4809	7.6576	0.0057	0.264
man/free	*employ/worker*	1.0200	0.4964	4.2222	0.0399	2.773
qualif_useful	*qualif_law*	-0.8744	0.5325	2.6961	0.1006	0.417
qualif_useless	*qualif_law*	-3.7764	0.8838	18.2576	<.0001	0.023

The results highlight that some covariates are significant in three of the four groups: the usefulness of the qualifications with respect to the type of job (Groups 1, 2 and 4), the level of job satisfaction (Groups 1, 2 and 3), and the accomplishment of at least one post-graduate internship/training programme (Groups 2, 3 and 4). Even the probability of an intense use of skills is positively influenced by the usefulness of graduates' qualifications, job satisfaction and accomplishment of at least one post-graduate internship/training programme.

Each group model is characterized by the presence of specific covariates. In Group 1, the probability that graduates on the lookout for a new job use their skills to a great extent are half the probabilities of their colleagues who did not expect to change activity; therefore, a poor job satisfaction stimulates young graduates to search for new jobs.

In Group 2, the professional role of graduates, the size of the firm and the graduation marks determine the use of skills. Those employed in small firms, with higher responsibilities, with high marks at graduation, have greater probability of using their university skills to a higher level than those with lower graduation marks who work in clerical or waged positions in large companies[12].

In Group 3, the self-employed and those working in public corporations show higher odds ratios than those working as employees and in private concerns; moreover, as the age is more advanced at graduation, the lower the probability is to use the expertise acquired at the university.

In Group 4, the only additional variable with regard to attendance in post-graduate internships/training programmes and the usefulness of the relative qualification is the professional status of the graduate: managers and freelancers show higher odds ratios than clerical and waged workers.

With regard to estimation of the model for the whole university, the results of the *score* test have suggested not to accept the hypothesis of proportional

[12] The effect of this covariate was very weak, so confirming the results of descriptive analyses that the final marks poorly discriminated among graduates because of a concentration of high values.

odds for the covariate represented by the groups of degree programmes. Hence, the model applied is a *partial proportional odds logistic model*, whose general structure is as follows:

$$\begin{cases} \text{logit}(P_{1i}) = \log\left(\frac{P_{1i}}{1-P_{1i}}\right) = \log\left(\frac{P_{1i}}{P_{23i}}\right) = \alpha_1 + \sum_{j=1}^{h} \beta_j \cdot x_{ji} + \beta_{1,h+1} \cdot x_{h+1,i} \\ \text{logit}(P_{12i}) = \log\left(\frac{P_{12i}}{1-P_{12i}}\right) = \log\left(\frac{P_{12i}}{P_{3i}}\right) = \alpha_2 + \sum_{j=1}^{h} \beta_j \cdot x_{ji} + \beta_{2,h+1} \cdot x_{h+1,i} \end{cases}$$

where x_{h+1} indicates the explicative variable (the *cluster* variable, in this case) for which the proportional odds hypothesis is not valid and for which $\beta_{1,h+1}$ and $\beta_{2,h+1}$ are the x_{h+1} coefficients of the first and second logit, respectively. In other words, the partial proportional odds model takes on proportional odds for only certain explicative variables and not for others.

Consequently, the two logits that compare $Y = 1$ with $(Y = 2) \cup (Y = 3)$ in the first case, and $(Y = 1) \cup (Y = 2)$ with $Y = 3$ in the second, are distinguishable not only because of the intercept but also of the value assumed by the regression coefficients for which no proportional odds had been assumed. Since Y assumes 3 categories, $e^{\beta_{1,h+1}}$ indicates the P_1 variation with respect to P_{23} with a, unitary increase x_{h+1}, while $e^{\beta_{2,h+1}}$ indicates the same variation that P_{12} undergoes with respect to P_3.

Once the significant variables have been selected and each of them submitted to the hypothesis of proportional odds, the final model for the whole university is estimated with the PROC GENMOD application of the SAS software, using Newton Raphson's maximization algorithm.

Table 5. Partial proportional odds ordered logistic models, for every group

Effect	*Reference*	*Estimate* P_{12}/P_3	*Estimate* P_1/P_{23}	*S.E.* P_{12}/P_3	*S.E.* P_1/P_{23}	*Odds ratio* P_{12}/P_3	*Odds ratio* P_1/P_{23}
Intercept	-	-0.9734		1.0523		-	
post_grad_no	*Post_grad_yes*	-0.2461		0.1075		0.782	
man/free	*employ/worker*	0.4661		0.1232		1.594	
large_firm	*small_firm*	-0.3375		0.1126		0.714	
qualif_useful	*qualif_law*	-3.2424		0.2072		0.353	
qualif_useless	*qualif_law*	-1.0422		0.1219		0.039	
sufficient_satisfy	*Very_satisfy*	-1.3017		0.1984		0.510	
little_satisfy	*very_satisfy*	-0.6732		0.1155		0.272	
agegrad	-	0.0410		0.0091		1.042	
Group 1	Group 2	-0.7510	-0.3904	0.2415	0.2683	0.472	0.677
Group 1	Group 3	0.0710	-0.4736	0.4187	0.4879	1.074	0.623
Group 1	Group 4	0.3125	-0.4561	0.3511	0.4335	1.367	0.634
Group 2	Group 3	0.8220	-0.0833	0.4156	0.4782	2.275	0.920
Group 2	Group 4	1.0635	0.1249	0.3531	0.4228	2.896	1.133
Group 3	Group 4	0.2415	0.0935	0.4893	0.5854	1.273	1.098

In Table 5, the selected covariates are listed with an indication of the effect compared to the category assumed as reference, followed by the estimated regression coefficients, the relative standard errors and the odds ratios[13]. Due to the non applicability of the hypothesis of proportional odds for the *cluster* variable, the estimates are given for both logits, that is, for P_{12}/P_3 and P_1/P_{23}.

The determinants of the use of skills are the type of study programme, the attendance of post-graduate internships/training programmes, the professional position, the size of the company, the use of the qualifications achieved, the satisfaction for the job, and the marks obtained upon graduation. The net effect exerted by the determinants of the proportional odds is similar to the effects revealed with by the analysis of the groups, even if covariates that were significant for single groups of study programmes (age at graduation, field of work, type of work, and search for a new job) were ignored in the general model.

The probability that a graduate belonging to Group 1 uses his/her skills to a high extent is approximately 33-37% less than that of colleagues belonging to the other groups; in contrast, the odds ratio for a graduate in Group 3 is 8.0% higher than that of graduates belonging to the other groups. The graduates belonging to Groups 2 have more of an advantage over Group 4 ($P_1/P_{23} = 1{,}133$) in job-hunting that conforms to the expertise acquired at university. However, both have higher odds ratios than their colleagues in Group 1 but lower than those in Group 3[14].

6. Two-level random intercept model: a comparison

The hierarchical structure of the data led to the adoption of a multilevel ordinal logistic model of regression in which the first level units were 2,882 employed graduates, whereas the second level units were 38 study programmes.

The explicative variables of the previous analysis were the first-level covariates, whereas the grouping variables of the study programmes served as

[13] The *p*-values do not exceed 2.2%. Though the *cluster* variable (*p*-value 0.0019) showed overall significance, some of the comparisons between groups were not significant. This problem could have been avoided with a further aggregation of the groups, but we preferred to present the results so to analyse the four original groups.

[14] The interpretation of the odds ratios that compare $(Y=1)\cup(Y=2)$ with $Y=3$, that is, P_{12}/P_3, is not so clear. The focus on one of the two odds ratios depends on the relevance given to the $Y=2$ intermediate response category: in the case P_1/P_{23} it is cumulated with the $Y=3$ mode, and has therefore a negative meaning, while in the other case P_{12}/P_3 it is added with the $Y=1$ mode, and is consequently positive. In our analysis, a negative meaning was considered more appropriate for $Y=2$, since this category represents a clear stand taken by the subject interviewed with regard to the questions asked, whereas the aim of our research is to pinpoint the study programmes characterized by their capacity to create skills useful for the labour market.

second-level covariates. We chose the model by estimating[15] the null model (that is, without explanatory variables) in order to assess the significance of the second-level residual variance. Through a stepwise procedure, the significant first and second-level covariates were selected as well as any quadratic terms and effects of interaction. A random intercept model with two levels of aggregation *(proportional odds*, see: Fielding *et al.,* 2003; Goldstein, 2003; Hedeker, 2004) was obtained.

The general structure for the k^{th} generic programme is the following:

$$\begin{cases} \log\left(\frac{P_{1ik}}{P_{23ik}}\right) = \log\left(\frac{P(Y_{ik} \le 1)}{P(Y_{ik} > 1)}\right) = \alpha_{1k} + \sum_{j=1}^{k} \beta_j \cdot x_{jik} \\ \log\left(\frac{P_{12ik}}{P_{3ik}}\right) = \log\left(\frac{P(Y_{ik} \le 2)}{P(Y_{ik} > 2)}\right) = \alpha_{2k} + \sum_{j=1}^{k} \beta_j \cdot x_{jik} \end{cases}$$

Since the α_{1k} and α_{2k} intercepts vary according to the degree programme,

$$\alpha_{1k} = \gamma_1 + U_{0k} \text{ and } \alpha_{2k} = \gamma_2 + U_{0k},$$

the model takes on the following form:

$$\begin{cases} \text{logit}(P_{1ik}) = \log\left(\frac{P_{1ik}}{1 - P_{1ik}}\right) = \log\left(\frac{P_{1ik}}{P_{23ik}}\right) = \gamma_1 + \sum_{j=1}^{h} \beta_j \cdot x_{jik} + U_{0k} \\ \text{logit}(P_{12ik}) = \log\left(\frac{P_{12ik}}{1 - P_{12ik}}\right) = \log\left(\frac{P_{12ik}}{P_{3ik}}\right) = \gamma_2 + \sum_{j=1}^{h} \beta_j \cdot x_{jik} + U_{0k} \end{cases}$$

where U_{0k} indicates the residual second-level component corresponding to the *k*-th group; it is assumed that the second-level residuals are normally distributed with zero mean and constant variance.

Because of the failure in the convergence of the log-likelihood algorithm, in some cases, and due to the non-significance of the estimates obtained in others, the estimated model has no random coefficients. The main consequence is that the net effect exerted by the explanatory variables for each study programme cannot be distinguished. On the other hand, our analysis allows the estimation of coefficients and the consequent detection of groups of covariates for every group of degree programmes.

The estimated model (Table 6) showed significant variability in the second-level residuals, and the adoption of a multilevel analysis is so justified. No second-level covariate resulted to be significant, probably because of the aggregation process of these variables.

With regard to the first-level covariates selected, five out of seven were also in the partial proportional odds logistic model and showed similar net effects.

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[15] The model was estimated via the PROC NLMIXED system of SAS software, by means of maximization of the log-likelihood function using the Dual Quasi-Newton algorithm and the Gaussian adaptive quadrature method.

Table 6. Two-level random intercept ordered logistic model (proportional odds)

Effect	*Reference*	*Estimate*	*Standard Error*	*Value t*	*p-value*	*Odds ratio*
FIXED EFFECTS						
Intercept 1	-	-0.0863	0.9022	0.10	0.9243	--
Threshold	-	-2.1287	0.0804	26.47	<0.0001	--
male	*Female*	-0.1962	0.0948	2.07	0.0453	0.8218
self_work	*employ_work*	-0.5353	0.1552	3.45	0.0014	0.5855
post_grad_no	*post_grad_yes*	-0.2008	0.0888	-2.26	0.0296	0.8181
man/free	*employ/worker*	0.7452	0.1460	-5.11	<0.0001	2.1069
qualif _useful	*qualif_law*	-1.0146	0.0994	10.20	<0.0001	0.3625
qualif _useless	*qualif_law*	-3.1033	0.1726	17.98	<0.0001	0.0449
sufficient_satisfy	*very_satisfy*	-0.7012	0.0948	7.40	<0.0001	0.4960
little_ satisfy	*very _satisfy*	-1.3428	0.1540	8.72	<0.0001	0.2611
gradmark	-	0.0172	0.0086	-2.01	0.0521	1.0174
RANDOM EFFECTS						
St.Dev. (U_{0k})	-	0.2904	0.06473	4.49	<0.0001	--

However, in contrast to what emerged in the previous analysis, the size of the firm was no longer significant; nonetheless, both the gender of the graduate and the self-employment activity became part of the model.

The probability of using skills to a wider extent resulted to be 18% greater among male graduates than female; the same probability was 42% less in the case of self-employed subjects as compared to employed colleagues. This relationship contradicts what emerged for the same variable in the logistic model referred to Group 3 (Table 4).

7. Conclusions

The two approaches adopted for detecting the determinants of the use of skills acquired by young graduates at university and for calculating their relative net effect led to similar conclusions. The higher the graduation mark, the greater the graduate's chance of finding a suitable position, and the more the graduate's qualification was useful for job-hunting, the more he/she may be satisfied with his/her job. Moreover, if he/she has accomplished at least one post-graduate internship/training programme and taken up a position entailing a certain degree of responsibilities (manager or free-lance) it is likely that he/she will be assigned tasks that require a satisfactory use of his/her skills.

Over and above these undoubtedly important conclusions, the analysis of groups permits more exhaustive considerations than those from the multilevel analysis. In the group of non-technical graduates, the search for a new job may be explained by the particularly poor usage of the university skills. The size of the firm and the professional position occupied are critical for the graduates in Engineering, Economics and Law who can choose between self-employment and employment. Lastly, physicians, dentists and chemists, who can be either self-employed or employed in public or private fields, is consistent with the type of work (self-employed or employed) and with the field of work (public or private).

The study programmes in the humanities and formative sciences are associated with a poor use of the skills acquired at university, those related to health are right the opposite, and technical study programmes are in the middle. We may point out a lack of coherence in the classification of some study programmes: the statistical programmes are classified in the first general group and the Educational science together the health group.

To conclude, even if the multilevel approach has a theoretical structure that takes into consideration the hierarchy of the data on graduates, it does not contribute significantly to the analysis of the phenomenon. Contrariwise, the mathematical complexity of the model and the optimisation algorithms, make it extremely difficult to estimate the random coefficients, which are essential for a comprehension of the effects of the second-level units (degree programmes) on the criterion variable.

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