Estimating the effect of remote teaching for university students through generalised linear mixed models

Stima dell'effetto della didattica a distanza per gli studenti universitari mediante modelli lineari misti generalizzati

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Abstract The present paper aims at analysing the effects of remote teaching on university students' careers, as a consequence of university closures due to the COVID-19 pandemic. For this purpose, we use administrative data of the University of Florence on students' careers and compare their performance in terms of the probability of passing specific exams. In particular, using a random intercept logit model, we compare the group of students enrolled in the academic year 2018/2019 – who received classic face-to-face teaching – with the group of students enrolled in the subsequent academic year, who experimented remote teaching during the second semester. Results obtained on different degree programs show that the effect of remote teaching at the course level is markedly heterogeneous, with different sign and magnitude.

Abstract *Il presente lavoro si propone di analizzare gli effetti della didattica a distanza sulla carriera degli studenti universitari, a seguito della chiusura delle università dovute alla pandemia di COVID-19. A tal fine, utilizziamo i dati amministrativi dell'Università di Firenze sulla carriera degli studenti e confrontiamo la loro*

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produttività in termini di probabilità di superare specifici esami. In particolare, utilizzando un modello logit a intercetta casuale, confrontiamo il gruppo di studenti iscritti all'a.a. 2018/2019 – che hanno frequentato la classica didattica frontale – con il gruppo di studenti iscritti all'a.a. successivo, che hanno sperimentato la didattica a distanza nel secondo semestre. I risultati ottenuti sui diversi corsi di studio mostrano che l'effetto della didattica a distanza a livello di insegnamento è marcatamente eterogeneo, con segno e grandezza differenti.

Key words: COVID-19, distance learning, logit model, random effects, university exams

1 Introduction

The COVID-19 pandemic has had a resonant impact in all aspects of social life. The educational field has been affected by the pandemic as well, due to schools and universities closure. Focusing on the academic world, universities are intensively dealing with the pandemic, whose effects consisted in an impact on enrolments, demands for large tuition cuts, redesign of courses and learning approaches by teachers. On the other side, students had to face with an uncertain environment due to financial and health shocks, as well as to the introduction of remote teaching activities, which contributed to jeopardise their university performance, educational plans, labour market participation, and in general expectations about future [2].

Several studies attempt to evaluate the impact of COVID-19 on higher education students' experiences, in particular on their academic performance [4, 6, 7, 5]. Although all these studies highlight their overall difficulties, they detect opposing results in terms of effects on students' performance.

However, existing works on the effects of remote teaching on the university students' performance are mainly based on specifically designed surveys. In this paper, we contribute to the research on the present topic by proposing a modelling approach that allows us to exploit use administrative data on students' career.

The approach is applied to data on passed exams about students' belonging to different degree programs at the University of Florence. In particular, we aim at comparing two cohorts of students: *i*. those enrolled in academic year 2018/2019, who did not experience remote teaching at all, and *ii*. those enrolled in the subsequent academic year 2019/2020, who experimented remote teaching only as regards the courses held in the second semester.

The comparison is performed separately for each degree program, by analysing students' performance in terms of probability of passing the exams of the courses envisaged by the degree program. Given that the same student has to take several exams (hierarchical data structure, with exams nested within students), a random intercept logit model is estimated and the remote teaching effect for each course is detected in terms of difference in the probability of passing the exams between the two cohorts.

The paper is organised as follows. Section 2 is dedicated to a description of the data and the statistical model used for the analyses, whose results are presented in Section 3. Finally, Section 4 draws some concluding remarks.

2 Data and proposed model

Data from the administrative archive of the University of Florence on students' careers are considered, including information on passed exams together with some students' background details (e.g., gender, high school type and grade). Data about students of the two cohorts (2018/2019 and 2019/2020) are extracted from the archive as regards the the following five bachelor degree programs: *i*. Chemistry; *ii*. Industrial design; *iii*. Law; *iv*. Mechanical engineering; *v*. Psychology. Descriptive statistics on these data are reported in Table 1.

Table 1 Share of students (%) that passed the exams related the courses envisaged in each degree program (second semester of the first year): comparison of observed raw outcomes between cohorts (sizes of cohorts in parenthesis).

Degree program	Credits	Course	Cohort 2018	Cohort 2019	Diff.
Chemistry	6	CHEM1	11.2	5.4	−5.8
($n_{2018} = 98$, $n_{2019} = 112$)	12	CHEM2	42.9	29.5	−13.4
	6	CHEM3	9.2	14.3	5.1
	6	CHEM4	27.6	23.2	−4.4
Industrial design	6	DES1	80.5	77.2	−3.3
($n_{2018} = 149$, $n_{2019} = 167$)	6	DES2	61.1	60.5	−0.6
	12	DES3	63.8	56.9	−6.9
Law	12	LAW1	57.3	53.0	−4.3
($n_{2018} = 347$, $n_{2019} = 421$)	9	LAW2	36.9	41.3	4.4
	9	LAW3	58.8	55.1	−3.7
Mechanical engineering	9	ENG1	47.1	57.2	10.1
($n_{2018} = 325$, $n_{2019} = 318$)	6	ENG2	14.8	22.0	7.2
	12	ENG3	44.0	23.6	−20.4
	12	ENG4	21.2	20.1	−1.1
Psychology	9	PSY1	77.5	72.1	−5.4
($n_{2018} = 427$, $n_{2019} = 426$)	9	PSY2	75.4	76.1	0.7
	6	PSY3	69.6	62.7	−6.9
	6	PSY4	66.0	71.4	5.4

Given the hierarchical structure of our data (exams to take nested within students), we consider a mixed model formulation. In particular, the response variable is the exam outcome (passed/not passed) of each student as regards the courses envisaged in the second semester of the corresponding degree program study plan (first year compulsory courses). Moreover, in order to control for differences among students of the two cohorts, we include a control variable in the model, namely the student's performance at the first semester.

Given degree program p with N_p enrolled students and M_p courses envisaged at the second semester of the first year, our dichotomous response variable, denoted by Y_{ij}, is equal to 1 if student i passes exam j, and 0 otherwise, with $i = 1,\ldots,N_p$ and $j = 1,\ldots,M_p$. In order to consider the correlation between exams of the same student, a generalised linear mixed model is employed for modelling the probability of passing exam j by student i, $P(Y_{ij} = 1)$:

$$\text{logit}(P(Y_{ij} = 1|\boldsymbol{x}_i, D_i)) = \gamma_j + \delta_j D_i + \boldsymbol{x}_i'\boldsymbol{\beta} + u_i, \tag{1}$$

where D_i is a dummy variable for the cohort (reference level is cohort 2018/2019) and $\boldsymbol{x}_i$ is the vector of student covariates. Specifically, two covariates are included in this model as regards the student's performance at the first semester, namely the proportion of gained credits and a dummy variable for students getting zero credits during the first semester.

The model at issue has an exam-specific intercept γ_j, while parameter δ_j represents the effect of remote teaching on exam j, as it is the variation in the model intercept between the two cohorts of students, that is, the difference on the logit of passing exam j between the two cohorts. Finally, random intercepts u_i are independent normally distributed, with zero mean and constant variance σ_u^2.

3 Results

Model (1) is fitted separately for students belonging to each degree program by means of the R package `lme4`[3]. However, given that the parameter of greatest interest δ_j – which represents the effect of the remote teaching on exam j – is on the logit scale, we compute the average marginal effect (AME)[1], that is, the average discrete difference in the probability of passing the exam between 2018/2019 and 2019/2020.

AMEs are reported in Table 2, together with the corresponding 95% confidence intervals. For example, looking at the first course of the Psychology degree program (PSY1), a negative and significant effect of remote teaching is detected. In fact, the related AME is -0.082, hence, when comparing cohort 2019/2020 with respect to cohort 2018/2019, the probability of passing this exam decreases, on average, by 8.2% (first semester performance being equal).

As can be noticed, both positive and negative effects can be highlighted in each degree program, although they are significant in few cases. In fact, in Chemistry, Industrial Design and Law, no significant effect (at 5%) emerges from the analysis, whereas the most pronounced effects are detected as regards students of Mechanical engineering and Psychology. Students of the former program have both positive (courses ENG1 and ENG2) and negative (ENG3) significant performance: in partic-

Table 2 Average Marginal Effects (AME) and 95% confidence interval (95% CI) by degree program from model (1)

Course	AME	95% CI
	Chemistry	
CHEM1	$-0.066^{\cdot}$	$(-0.135, 0.002)$
CHEM2	-0.034	$(-0.089, 0.022)$
CHEM3	$0.079^{\cdot}$	$(-0.003, 0.161)$
CHEM4	0.017	$(-0.048, 0.081)$
	Industrial design	
DES1	0.064	$(-0.026, 0.155)$
DES2	$0.066^{\cdot}$	$(-0.009, 0.141)$
DES3	0.013	$(-0.068, 0.094)$
	Law	
LAW1	$-0.053^{\cdot}$	$(-0.108, 0.002)$
LAW2	0.036	$(-0.018, 0.090)$
LAW3	-0.046	$(-0.102, 0.009)$
	Mechanical engineering	
ENG1	0.096^{**}	$(0.040, 0.152)$
ENG2	0.108^{**}	$(0.043, 0.174)$
ENG3	-0.167^{***}	$(-0.225, -0.110)$
ENG4	0.010	$(-0.054, 0.073)$
	Psychology	
PSY1	-0.082^{**}	$(-0.133, -0.030)$
PSY2	-0.017	$(-0.065, 0.031)$
PSY3	-0.086^{***}	$(-0.134, -0.038)$
PSY4	0.025	$(-0.019, 0.068)$

Significance levels: *** = 0.001; ** = 0.01; * = 0.05; $^{\cdot}$ = 0.10

ular, for this latter course, the greatest (in absolute value) effect of remote teaching is outlined, equal to -0.167. Finally, two significant and negative effects of the same magnitude (around -0.08) are detected for Psychology.

4 Conclusions

Due to COVID-19 pandemic, universities have had to employ emergency strategies to carry out teaching activities, such as switching from face-to-face to remote teaching. However, its implementation within the same university can be very heterogeneous, as teachers could customise their online courses, despite the availability of general guidelines at the university level. Consequently, remote teaching effect on students' performance can be pretty multifaceted.

Relying on the generalised linear mixed modelling framework, we studied the effect of remote teaching at the single course level, by exploiting the administrative archive on students' careers of the University of Florence. Specifically, we compared the performance (in terms of probability of passing an exam) of students belonging to different bachelor's degree programs and from two separate cohorts, of which only one experienced remote teaching.

As expected, our analysis underlined negative and positive remote teaching effects among different degree programs and, also, within the same degree program, even if the detected effects were not significant in most cases.

The present work presents some drawbacks. Firstly,the outcome is based on exam results, but we are aware that passing the exam can only be considered a proxy of learning achievement. Secondly, the analysis does not allow us to separate remote teaching effect from the impact of new exam rules, as the data do not include details on the examination modalities.

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