

# The impact of combining work with study on the labour market performance of graduates: the joint role of work intensity and job-field match

Antonio Di Paolo

*Departament d'Econometria, Estadística i Economia Aplicada and AQR-IREA, Universitat de Barcelona, Barcelona, Spain, and*

Alessia Matano

*Department of Economics and Law, University of Rome "La Sapienza", Rome, Italy and*

*AQR-IREA, Universitat de Barcelona, Barcelona, Spain*

## Abstract

**Purpose** – This paper investigates the effects of working during university education on labour market outcomes of university graduates.

**Design/methodology/approach** – Based on data from three successive cohorts of graduates from the Spanish region of Catalonia, the authors estimate the effect of having worked in different types of jobs before graduation, classified according to work intensity and the match with the field of study, on the probability of being employed, having a permanent contract or having a job that requires the specific degree four years after graduation. The authors employ a multinomial endogenous treatment model that enables controlling for self-selection into pre-graduation working activities.

**Findings** – Pre-graduation work activities that are related to the field of study are generally beneficial for employability and job stability. Work experiences unmatched with the degree's content are detrimental for graduates' job–education match.

**Originality/value** – This is the first paper that jointly considers the role of work intensity (part-time vs full-time) and the relationship with the field of study in a framework that accounts for self-selection into different types of jobs. The authors also contribute to the literature by estimating the effect of pre-graduation jobs not only on the chances of being employed four years after graduation but also on two important aspects of job quality: having a permanent contract and having a job that requires the specific degree.

**Keywords** University graduates, Pre-graduation jobs, Employability, Job quality, Self-selection

**Paper type** Research paper

## JEL Classification — I23, J24, J22

© Antonio Di Paolo and Alessia Matano. Published by Emerald Publishing Limited. This article is published under the Creative Commons Attribution (CC BY 4.0) licence. Anyone may reproduce, distribute, translate and create derivative works of this article (for both commercial and non-commercial purposes), subject to full attribution to the original publication and authors. The full terms of this licence may be seen at <http://creativecommons.org/licences/by/4.0/legalcode>

The authors express gratitude to participants in the EALE Conference, Applied Economics Meeting, LEER Workshop on Education Economics, AIEL Conference, Jornadas de Economía Laboral, Symposium of the Spanish Economic Association, Lisbon Research Workshop on Economics, Statistics and Econometrics of Education, Catalan Economic Society. This research was partially funded by “la Caixa” Foundation through the competitive call LL2019-5 “Call to support social research projects: vocational training, early school leaving and job insecurity”, and by the Spanish Ministry of Finance, Industry and Competitiveness (project ECO2016-75805-R). The usual disclaimers apply.



---

## 1. Introduction

The investment in higher education represents an important decision for enhancing individuals' socioeconomic status throughout the life cycle. In fact, university graduates generally enjoy better labour market outcomes relative to less educated workers and tend to find employment more quickly than young individuals with lower levels of education (Pastore *et al.*, 2022). However, a growing amount of evidence highlights the existence of significant differentials in employability, remuneration and job quality among individuals with tertiary education. On the one hand, the field of study represents one of the key elements behind such differentials since different college majors are differently rewarded in the labour market (Altonji *et al.*, 2016). On the other hand, there are significant disparities in career performance also among graduates who have obtained the same degree. This is because graduates' career success depends not only on the overall quality of higher education, but also on the amount of human capital, skills and valuable experience that are acquired while enrolled at university, which ultimately depends on students' choices. In this respect, a fundamental aspect concerns the decision to exclusively focus on studying, or to combine university education with some kind of work activity, which might be beneficial to future labour market outcomes. In fact, the choice to engage in some kind of work activity during university—besides forced decisions due to financial constraints—is generally motivated by the willingness to gain work experience and related competences that could improve post-graduation job opportunities and reduce the length of school-to-work transition (Pastore *et al.*, 2021). Indeed, from a theoretical point of view, pre-graduation employment should improve future employability because, on the one hand, it shapes students' general and specific human capital through the acquisition of relevant work experience as well as cognitive and non-cognitive skills that increase productivity in the workplace. On the other hand, student work, especially when work activities are related to the content of university degree, could generate positive signals that improve hiring chances and the number of offers when searching for a job [1].

Nonetheless, there is an important trade-off that should be taken into account when taking the decision to work while studying, since this could divert students' effort away from academic learning, which in turn might have a negative effect on employability.

Empirically, the effects of pre-graduation employment have been widely investigated in the last decades. Most of the existing works focused on the impact of student work on academic performance. The overall results from this literature point out that working while studying generally has detrimental effects on academic outcomes, mostly in terms of increased likelihood of student dropout and—to a lesser extent—late graduation [2].

A smaller but growing number of papers investigate the impacts of work experiences acquired whilst pursuing a university degree on subsequent graduates' employability, using either experimental or non-experimental data [3]. The general findings point out that pre-graduation work experiences matter for future employability, job quality and earning potential. Overall, the beneficial effect of student work represents a combination of increased human capital and signalling, but the extent of these positive impacts is likely to depend on specific characteristics of the job performed during higher education. In particular, on the one hand, work intensity (e.g. part-time vs full-time employment, occasional vs regular jobs, etc.) appears to be relevant, with higher effect found for full-time jobs. On the other hand, and most importantly, the relationship between the job performed and the field of study reveals to be crucial for the chances of employability after graduation and job quality outcomes. Indeed, pre-graduation jobs related to students' degree are consistently found to be beneficial for several employability and job quality measures. This is clearly the case for internship programmes, which are generally connected with the content of the university degree, and are increasingly becoming mandatory activities in many university degrees around the world.

With this paper, we contribute to the existing research by estimating the impact of working in jobs characterised by different combinations of work intensity and relationship

with the field of study in a framework that deals with self-selection into pre-graduation employment. To the best of our knowledge, there are no papers based on non-experimental data that analyse jointly the effect of being involved in a job of a given intensity (i.e. part-time or full-time), which is related or not to the field of study, on post-graduation employability. We believe that these two job features should be jointly considered in an empirical analysis, since different combinations of work intensity and job-field match could lead to different payoffs—relative to full-time students—in terms of labour market outcomes. Hence, with this paper we try to fill this gap in the literature. Moreover, we contribute to the empirical literature by analysing the effect of types of pre-graduation work experiences not only on the probability of being employed after completing the degree, but also on two relevant outcomes that characterise job quality: having a permanent contract and performing a job that requires the specific degree (i.e. an indicator of job-education match).

We use data from three successive waves of the “Survey on Labour Market Outcomes of University Graduates” (2011, 2014 and 2017), which include information on graduates from public universities of the Spanish region of Catalonia who completed their degree four years before (2007, 2010 and 2013). The Spanish case is an interesting case study, given the worrying figures about the youth labour market in Spain: high risk of unemployment (also among highly educated individuals), prevalence of temporary employment and significant incidence of over-qualification and skills mismatch (see [Dolado \*et al.\*, 2013](#)). Therefore, a better understanding of the factors that could protect graduates’ economic potential against unfavourable labour market conditions is a key issue for future policies aimed at promoting employability of recent graduates.

The data contain a wide set of information on individual academic, socio-demographic and labour market characteristics. In particular, they provide information on the working status of students during the last two years before graduation, which is classified according to work intensity (part-time and full-time) and relationship with the field of study (related or unrelated). We analyse, first, the impact of different types of pre-graduation work activities on the probability of being employed four years after graduation. Second, we explore the effects of working while studying on two measures of job quality, namely the likelihood of having a permanent contract and performing a job that requires the specific degree obtained.

We start by running simple OLS regressions, which provide conditional correlations between pre-graduation working activities and the outcomes of interest. The results obtained by OLS indicate that working while studying positively correlates with better labour market performance. However, as widely discussed in the literature, OLS estimates are likely to be biased due to self-selection into work activities. In fact, there are unobserved factors that might simultaneously affect the probability of working while studying and employment performance, such as individuals’ cognitive and non-cognitive abilities, motivation or expectations.

In this paper, we control for self-selection through the estimation of a multinomial endogenous treatment model ([Deb and Trivedi, 2006](#)), using as instrument a novel variable: a measure of local employment potential. The results obtained by employing the multinomial endogenous treatment model reveal that selection based on unobservable traits strongly matters. More specifically, after controlling for self-selection, the probability of being employed after four years from graduation is significantly higher only for graduates who have been working in occupations related to their field of study compared to full-time students, regardless of work intensity. The likelihood of having a permanent job is generally significantly higher for graduates who had a job before completing the degree, but the effect is stronger for working activities related to the field of study. This result indicates that the beneficial effect of working while studying on future job stability seems to be mostly driven by the accumulation of occupation-specific skills. Finally, working in jobs unrelated to the field of study, especially part-time jobs, increases the risk of job-education mismatch at the early stage of the career, since the probability of having a position that requires the specific degree is significantly lower relative to

---

full-time students. Overall, these findings point out the primary importance of working in jobs related to the field of study while enrolled in higher education to improve graduates' labour market outcomes. Moreover, our paper highlights the relevance of categorising pre-graduation working activities along different dimensions and confirms the need to account for self-selection based on unobservable traits to properly estimate the impact of combining undergraduate studies and work on future employability. Therefore, the evidence reported in this paper reinforces the policy implications emerging from recent works on the issue of working while studying, suggesting that academic policymakers should foster student work in occupations related to the field of education to generate an important value added in terms of human capital, cognitive and non-cognitive skills and relevant work experience for university students. The introduction of compulsory internship programmes as part of the learning process in several university degrees indeed represents a sensible route to follow. The structure of the paper is as follows. In [Section 2](#), we review the existing literature on the relationship between working while studying and labour market performances. In [Section 3](#), we describe the data and present some descriptive statistics. [Section 4](#) explains the details of the empirical strategy, while [Section 5](#) reports the main results. The conclusions are drawn in [Section 6](#).

## 2. Related literature

What do we know so far about the effect of working while studying on post-graduation labour market outcomes? Although there are several, possibly complementary, theoretical reasons to consider that university students' work pays off in the labour market, the existence and the amount of such return is ultimately an empirical question, which represents the focus of several papers published over the last two decades. Most of the papers have a descriptive nature and rely on conditional correlations, since they do not take into account self-selection into pre-graduation work activities. [Molitor and Leigh \(2005\)](#) estimate the wage return to each additional year of in-school work experience, both at the high school and college level. They reported that work experience acquired while in education among US graduates, especially in two-year colleges, positively correlates with future wages. [Geel and Gellner \(2012\)](#) explicitly consider whether pre-graduation jobs are related or not to the field of study and report that only having worked in matched jobs correlates with graduates' labour market outcomes (i.e. higher earnings, lower job search duration and risk of unemployment). Similarly, [Weiss \*et al.\* \(2014\)](#) analyse the effect of student work among German graduates and found that only voluntary jobs related to the field of study are beneficial for employability, while unmatched jobs may even be detrimental in some cases. This evidence is confirmed in the multi-country study by [Passaretta and Triventi \(2015\)](#), who analyse the conditional correlation between working while studying, also taking into account the relationship with the degree. Their results indicate that experiencing any kind of pre-graduation work activities is negatively associated with the probability of being unemployed in Italy and Spain, while a negative correlation with the risk of skill mismatch emerges for jobs related to the degree. However, negligible or no relationships are found for Germany and for Finland. Finally, [Sanchez-Gelabert \*et al.\* \(2017\)](#), using data regarding graduates from Catalan universities, find a positive correlation between a single indicator of working while studying that does not take into account both work intensity and the match with the degree's contents, and a composite measure of employability.

However, as already stressed, the estimates reported in these studies are unlikely to represent causal relationships, since they use non-experimental data in which observed pre-graduation work activities may be impacted by potentially endogenous choice of the students. In particular, there are several unobserved students' characteristics that might jointly affect both the propensity to work before completing the university degree and future labour market outcomes. To tackle this issue, some authors apply different empirical strategies to deal with the problem of students' selection based on unobservable

characteristics, in order to provide causal estimates of the returns to work while studying [4]. The first work that highlights the importance of accounting for unobservable traits when estimating the effect of student work on academic performance is the paper by Hotz *et al.* (2002). Thanks to the availability of longitudinal data, they account for unobserved heterogeneity using a dynamic model to estimate the wage return to part-time and full-time employment among US graduates. The results show a general positive effect of working activities and wages. Also, Hakkinen (2006) estimates IV regressions using local unemployment rate as instrument for pre-graduation work activities and finds that working before graduation generates a positive wage return among Finnish university graduates, with this effect declining with years from graduation. More recently, Margaryan *et al.* (2020) use an identification strategy based on the compulsory nature of internship experiences at the university programme level as source of exogenous variation. Their IV approach identifies the causal effect of student internship among those for whom this type of work experience was mandatory at degree level, and indicates that this specific work experience is rewarded in terms of earnings both in the short and medium term and reduces the risk of unemployment after graduation.

Overall, the results reported in this latter group of papers that deal with the issue of self-selection confirm the existence of positive returns to working while studying and highlight the importance of dealing with selectivity issues. Nonetheless, none of these works take into account the role played by both work intensity and, most importantly, the match with the degree. In this paper, we aim at filling this gap in the literature, by estimating the effect of different types of pre-graduation job activities, classified according to work intensity and match with the degree, in a framework that controls for self-selection into student work.

Although the majority of existing papers rely on non-experimental data proceeding from surveys, other recent works exploit experimental setups. The issue of self-selection is solved by the experimental nature of the data, in which pre-graduation working activities are randomly allocated either according to lotteries or to field experiments. Le Barbanchon *et al.* (2020) make use of the Uruguayan programme that assigns jobs in public-owned firms for one year to university students according to the results of a lottery. Although the match between selected students and jobs is mostly done according to compatibility with study intensity (rather than on job-degree match), the authors report positive causal estimates of student work on earnings and employment during the subsequent four years. Other papers rely on field experiments, through the random allocation of student jobs in fictitious resumes that are sent to available job advertisements. The first analysis based on this alternative methodology is Baert *et al.* (2016), who sent fake CVs to job vacancies in Flanders. In this paper, pre-graduation work experiences of recent university graduates are classified either as related or unrelated to the field of study. Moreover, the unrelated jobs could be performed either during the entire academic year or limited to the summer season. The authors report no significant differences in call back rates relative to CVs with no work experience, possibly because (hypothetical) jobs related to the degree were performed during the summer only. Nunley *et al.* (2016) perform a similar field experiment in the US labour market, but specifically consider student internship experiences. They report a significantly higher call back rate for resumes with internship. In another experiment, Baert *et al.* (2021) also analyse the effect of voluntary internship experiences (in Flanders) and find a positive effect on the chances of being contacted for a job interview, which is generally homogeneous with respect to several characteristics included in the fictitious resume. This evidence indicates that students working in internship programmes that are likely to be related (at least to some extent) to the degree field of study, generates positive signals in the labour market in terms of increasing the rate of job offers while searching for employment. Finally, the recent paper by Van Belle *et al.* (2020) specifically focuses on what student work signals in the CV, and provides novel evidence based on an experimental study using vignettes. They adopt a similar definition of

---

pre-graduation jobs as in [Baert \*et al.\* \(2016\)](#) and try to understand which skills are signalled by different types of work activities. Their results indicate that summer jobs increase the interview rate (which is somewhat at odd with the results from other experiments). Moreover, they report that any kind of job generates signals of better horizontal skills (work attitude, sense of responsibility and maturity, increased motivation and larger social capital), but only pre-graduation jobs related to the degree generate positive signals of increased skills and better trainability. Overall, the experimental evidence confirms the existence of positive returns in the labour market of pre-graduation work activities especially when they are matched to the degree's content, since this kind of work experience not only increases graduates' endowment of human capital and skills, but also generates additional valuable signals that matter for the job search.

### 3. Data and descriptive statistics

The empirical analysis is based on data from three successive waves of the "Survey on Labour Market Outcomes of University Graduates", which is implemented by the Quality Assurance Agency for the Catalan University System (AQU). The AQU survey takes place every three years (starting from 2001) and is administered to individuals born in Spain who graduated four years before in any of the seven public universities of the Spanish region of Catalonia [\[5\]](#). We use the data from the last three waves of 2011, 2014 and 2017 – covering bachelor graduates in 2007, 2010 and 2013 respectively – since they contain homogeneous information for our key variables.

The AQU survey contains information on individuals' socio-demographic characteristics, pre-graduation work activities, as well as labour market outcomes such as employment status, type of job, required qualification and type of contract that refer to the year in which the survey takes place (i.e. four years after graduation). Moreover, the AQU survey provides administrative information about the year of graduation, the specific degree obtained, the university of graduation and the municipality of residence during university attendance. The latter variable, as explained in the next section, represents an important value added of the AQU survey and is of crucial importance for our identification strategy.

Our main explanatory variable concerns work experiences while completing the degree. The information is obtained from the answer to the question "have you worked during the last two years of your academic career?". The survey allows for five mutually exclusive answers: (1) no, I was a full-time student; (2) yes, I had a part-time job related to the degree; (3) yes, I had a part-time job not related to the degree; (4) yes, I had a full-time job related to the degree and (5) yes, I had a full-time job not related to the degree [\[6\]](#). Therefore, with this information, we are able to classify pre-graduation jobs according to both work intensity and job-field match. This categorisation, to the best of our knowledge, has never been considered in previous studies on this topic.

Regarding labour market outcomes, we consider employment status and two variables reflecting job quality: having a permanent contract (vs fixed-term contracts or other situations [\[7\]](#)) and the qualification required for the current job, in particular, if it is the specific university degree.

For the purposes of our empirical analysis, we restrict the sample to individuals who graduated when they were at most 30 years old (in order to avoid including individuals in an advanced stage of their career) and we exclude individuals who enrolled at the university while being employed in the occupation they hold in the year of the survey. Graduates in Medicine are also excluded, because they are involved in a compulsory specialisation internship four years after graduation. We excluded observations with missing values in relevant variables and we retained only individuals who resided in Catalonia while studying

(88% of the whole sample), since this is a necessary requirement for the instrument that we use to rule out self-selection into working situations before graduation. In this way, we end up with a final pooled sample of 24,704 observations for the empirical analysis.

Descriptive statistics for the set of variables used in the empirical analysis are reported in Table 1, for the pooled sample and separately by wave. The raw data indicates that about 89% of individuals in our sample were employed at the time of the survey, a proportion that is quite stable across waves. Nonetheless, the incidence of permanent contracts among those who are working (53% for the pooled sample) decreases over time, reflecting the effects of the economic crisis that severely hit the Spanish labour market. Furthermore, 62% of employed individuals work in a job well matched with the obtained qualification, although this percentage is slightly decreasing across waves (from 65% in 2011 to 62% in 2017).

Regarding our main independent variable of interest, the data highlight that combining some kind of job with college is a common situation among individuals in our sample, since

% Of total sample	Pooled sample 33%		Wave 2011 34%		Wave 2014 34%		Wave 2017 40%	
	Mean	s.d	Mean	s.d	Mean	s.d	Mean	s.d
Employed	0.89	0.32	0.89	0.31	0.87	0.34	0.90	0.30
Permanent contract	0.53	0.50	0.58	0.49	0.51	0.50	0.51	0.50
Specific university degree required	0.62	0.48	0.65	0.48	0.61	0.49	0.62	0.49
Full-time student	0.35	0.48	0.33	0.47	0.34	0.47	0.39	0.49
Part-time job – related to the field of study	0.29	0.45	0.28	0.45	0.32	0.47	0.25	0.44
Part-time job – not related to the field of study	0.21	0.40	0.17	0.37	0.20	0.40	0.25	0.43
Full-time job – related to the field of study	0.12	0.32	0.17	0.37	0.10	0.31	0.08	0.27
Full-time job – not related to the field of study	0.04	0.19	0.05	0.22	0.03	0.18	0.03	0.18
Male	0.40	0.49	0.39	0.49	0.40	0.49	0.42	0.49
Age	28.42	2.25	28.60	2.26	28.42	2.31	28.24	2.15
Highest parental education = primary or less	0.29	0.46	0.34	0.47	0.31	0.46	0.24	0.43
Highest parental education = secondary	0.31	0.46	0.31	0.46	0.30	0.46	0.31	0.46
Highest parental education = tertiary	0.40	0.49	0.35	0.48	0.39	0.49	0.45	0.50
Field of study = humanities	0.04	0.20	0.05	0.22	0.04	0.19	0.04	0.20
Field of study = language	0.05	0.21	0.05	0.22	0.04	0.20	0.05	0.21
Field of study = art	0.01	0.11	0.01	0.09	0.01	0.08	0.02	0.14
Field of study = business and economics	0.13	0.34	0.12	0.33	0.14	0.35	0.13	0.34
Field of study = law, sociology and political sciences	0.11	0.32	0.12	0.32	0.10	0.30	0.12	0.33
Field of study = communication and journalism	0.05	0.21	0.05	0.22	0.05	0.22	0.04	0.20
Field of study = education	0.12	0.32	0.11	0.32	0.13	0.34	0.11	0.31
Field of study = social work	0.03	0.18	0.03	0.17	0.04	0.19	0.03	0.17
Field of study = biology, geology and environmental sciences	0.07	0.25	0.06	0.24	0.07	0.25	0.07	0.25
Field of study = chemistry, physics, maths and statistics	0.04	0.19	0.05	0.21	0.04	0.19	0.03	0.18
Field of study = health (excluding medicine)	0.04	0.18	0.03	0.17	0.04	0.19	0.04	0.19
Field of study = psychology and related degrees	0.04	0.20	0.03	0.17	0.03	0.18	0.06	0.23
Field of study = pharmacy, biomedicine and veterinary	0.03	0.17	0.02	0.15	0.02	0.15	0.04	0.20
Field of study = architecture and construction	0.05	0.21	0.05	0.21	0.04	0.21	0.05	0.22
Field of study = industrial, chemical and electronic engineering	0.09	0.29	0.09	0.29	0.09	0.29	0.09	0.29
Field of study = telecommunication and informatics	0.08	0.27	0.10	0.30	0.09	0.28	0.05	0.23
Field of study = agricultural engineering and related	0.02	0.15	0.03	0.16	0.03	0.17	0.01	0.12
Number of observations	24,704		8,032		8,298		8,374	

**Table 1.**  
Descriptive statistics,  
pooled sample and  
by wave

**Note(s):** Age refers to the survey year; descriptive statistics about the university of graduation are not reported in the table to accomplish with the rules of the contract for data transfer

only 35% of students declare not to have been involved in working activities during the last two years of undergraduate studies. The majority of those who work while studying is employed in part-time jobs, mainly related to their field of education (29%), although an important share of graduates work in occupations unrelated to their university degree (21%). Those employed in full-time jobs account for 16% of students, and are mainly employed in jobs related to the field of education. In [Table 2](#), we report descriptive statistics by working

The impacts of combining work with study

	Full-time student		Part-time job related		Part-time job not related		Full-time job related		Full-time job not related	
	Mean	s.d	Mean	s.d	Mean	s.d	Mean	s.d	Mean	s.d
Employed	0.87	0.34	0.91	0.29	0.87	0.33	0.92	0.27	0.86	0.35
Permanent contract	0.47	0.50	0.57	0.50	0.50	0.50	0.67	0.47	0.60	0.49
Specific university degree required	0.64	0.48	0.68	0.47	0.55	0.50	0.65	0.48	0.41	0.49
Wave 2011	0.31	0.46	0.32	0.47	0.26	0.44	0.47	0.50	0.43	0.50
Wave 2014	0.32	0.47	0.38	0.48	0.33	0.47	0.30	0.46	0.27	0.45
Wave 2017	0.37	0.48	0.30	0.46	0.41	0.49	0.22	0.42	0.29	0.46
Male	0.41	0.49	0.43	0.49	0.32	0.47	0.47	0.50	0.41	0.49
Age	27.76	1.96	28.60	2.20	28.38	2.17	29.55	2.46	29.88	2.40
Highest parental education = primary or less	0.26	0.44	0.29	0.45	0.32	0.47	0.36	0.48	0.36	0.48
Highest parental education = secondary	0.30	0.46	0.31	0.46	0.32	0.46	0.31	0.46	0.32	0.47
Highest parental education = tertiary	0.44	0.50	0.41	0.49	0.36	0.48	0.33	0.47	0.32	0.47
Field of study = humanities	0.04	0.20	0.02	0.15	0.09	0.28	0.01	0.10	0.08	0.27
Field of study = language	0.05	0.22	0.05	0.21	0.05	0.23	0.02	0.12	0.06	0.23
Field of study = art	0.01	0.11	0.01	0.08	0.02	0.14	0.00	0.05	0.01	0.08
Field of study = business and economics	0.12	0.32	0.14	0.35	0.09	0.29	0.24	0.43	0.12	0.32
Field of study = law, sociology and political sciences	0.10	0.31	0.08	0.27	0.16	0.36	0.10	0.30	0.24	0.43
Field of study = communication and journalism	0.05	0.21	0.06	0.23	0.05	0.21	0.03	0.18	0.04	0.19
Field of study = education	0.12	0.32	0.13	0.34	0.12	0.33	0.09	0.28	0.10	0.30
Field of study = social work	0.02	0.14	0.03	0.18	0.05	0.21	0.04	0.19	0.04	0.21
Field of study = biology, geology and environmental sciences	0.10	0.30	0.03	0.17	0.08	0.27	0.03	0.17	0.03	0.18
Field of study = chemistry, physics, maths and statistics	0.05	0.22	0.03	0.17	0.04	0.19	0.03	0.16	0.03	0.18
Field of study = health (excluding medicine)	0.04	0.19	0.03	0.17	0.04	0.19	0.04	0.20	0.02	0.13
Field of study = psychology and related degrees	0.04	0.20	0.03	0.16	0.07	0.25	0.02	0.12	0.06	0.24
Field of study = pharmacy, biomedicine and veterinary	0.04	0.20	0.03	0.17	0.02	0.14	0.02	0.14	0.01	0.10
Field of study = architecture and construction	0.04	0.19	0.08	0.26	0.02	0.15	0.06	0.25	0.02	0.13
Field of study = industrial, chemical and electronic engineering	0.09	0.29	0.11	0.31	0.05	0.22	0.13	0.34	0.07	0.26
Field of study = telecommunication and informatics	0.07	0.25	0.12	0.32	0.04	0.19	0.12	0.32	0.05	0.21
Field of study = agricultural engineering and related	0.02	0.15	0.02	0.15	0.02	0.14	0.03	0.17	0.03	0.16
Number of observations	8,735		7,047		5,089		2,869		964	

**Note(s):** Age refers to the survey year; descriptive statistics about the university of graduation are not reported in the table to accomplish with the rules of the contract for data transfer

**Table 2.** Descriptive statistics by working situation before graduation

situation before completing the degree. It can be noted that four years after graduation, working while studying is generally associated with better labour market outcomes, even if there are differences according to both job intensity and the relationship between the job and the field of study. In fact, the unconditional probability of being employed is higher among graduates who have worked in jobs related to their field of education (91–92%). Moreover, the incidence of permanent contract among employed graduates who were already working before completing the degree is generally higher than for full-time students, especially for those working full-time in a job that matches the field of their degree (67% against 47% for full-time students). More remarkably, graduates working in occupations unrelated to their field before completing the university degree are less likely to have a job that requires their specific degree after graduation (between 41% and 55%). On the contrary, those who worked in occupations related to their field of study during university have similar chances to have a job that requires their specific degree compared to full-time students (65–68% relative to full-time students, 64%).

#### 4. Empirical methodology

The starting point of our empirical analysis consists in estimating OLS equations that explain each labour market outcome as a function of exogenous covariates and indicators for different working situations before completing the degree. More specifically, we consider that each outcome ( $Y_i$ ) depends on pre-determined individual characteristics included in the vector  $X_i$  (gender, age and parental education), field of study and university fixed effects ( $\theta_f$  and  $\pi_u$  respectively), wave dummies ( $\tau_w$ ) and a set of indicators for each possible pre-graduation working status ( $W_i = j$ ) taking as reference category full-time students ( $j = 0$ ):

$$Y_i = \alpha + \beta' X_i + \sum_{j=1}^J \gamma_j I(W_i = j) + \theta_f + \pi_u + \tau_w + u_i \quad (1)$$

We estimate Equation (1) considering as dependent variable(s): (1) a dummy for being employed, (2) an indicator for having a permanent contract, (3) an indicator that takes the value of one if the specific degree was required during the hiring process.

However, OLS estimates of the  $\gamma_j$  parameters are consistent only if the unobservable factors that affect the propensity to work in a specific kind of job during the degree are unrelated to the error term of each outcome, which is unlikely to be the case, as suggested by previous empirical works. Indeed, unobservable traits – such as cognitive and non-cognitive abilities, motivation, expectation, etc. – could affect both the decision to work and any of the outcomes that we consider in this paper.

In order to control for the self-selection bias due to unobservable characteristics, we rely on the estimation of a multinomial endogenous treatment model (proposed by [Deb and Trivedi, 2006](#)), which allows to jointly model working decisions before graduation and labour market outcomes. A similar approach was previously applied by [Triventi \(2014\)](#), who analysed the impact of working while studying on academic performance, allowing for selection into full-time or part-time jobs (vs only studying). This represent a suitable estimation strategy for our purposes, given the multinomial nature of the variable describing pre-graduation jobs (which does not allow the estimation by standard IV as in [Hakkinen \(2006\)](#) and [Margaryan et al. \(2020\)](#), for example) and the lack of longitudinal data that would enable for a dynamic specification to deal with unobserved heterogeneity (as in [Hotz et al. \(2002\)](#), among others [8]).

Therefore, we exploit the available information in our dataset, in which pre-graduation jobs are classified according to work intensity and their relationship with the degree's content. Specifically, we consider that the choice of working status follows a mixed multinomial logit distribution, which means that the probability of observing individual  $i$  in working status  $j$  can be described as:

$$\begin{aligned} & \Pr(W_{im} = j | X_i, Z_m, \theta_j, \pi_u, l_{ij}) \\ &= \frac{\exp(\mu_j + \psi'_j X_i + \varphi_j Z_m + \theta_{fj} + \pi_{uj} + \tau_{wj} + \delta_j l_{ij})}{1 + \sum_{k=1}^J \exp(\mu_k + \psi'_k X_i + \varphi_k Z_m + \theta_{fk} + \pi_{uk} + \tau_{wk} + \delta_k l_{ik})}. \end{aligned} \quad (2)$$

Equation (2) shows that the likelihood of being assigned to the working status  $j$  for the individual  $i$  residing in municipality  $m$  depends on a set of observed individual characteristics ( $X_i$ ), a measure of local employment potential ( $Z_m$ , described below), field of study [9] and university fixed effects ( $\theta_f$  and  $\pi_u$ ), wave dummies ( $\tau_w$ ) and latent factors  $l_{ij}$  that proxy the unobserved individual heterogeneity affecting the propensity of having a certain kind of job before graduation (relative to full-time students) [10]. The selectivity-corrected outcome equation becomes:

$$Y_{im} = \alpha + \beta' X_i + \sum_{j=1}^J \gamma_j I(W_{im} = j) + \theta_f + \pi_u + \tau_w + \sum_{j=1}^J \lambda_j l_{ij} + \varepsilon_{im} \quad (3)$$

which corresponds to Equation (1) augmented by the latent factors  $l_{ij}$ , capturing the unobserved factors determining the decision to work while studying that also affect the final outcome. The associated factor loadings  $\lambda_j$  can be interpreted as selection terms, which capture the correlation between the unobservable determinants of having a given kind of job (relative to being a full-time student) and each of the outcomes we analyse. A positive (negative)  $\lambda_j$  coefficient indicates that the working status  $j$  and the outcome are positively (negatively) correlated through unobserved individual characteristics, indicating the existence of positive (negative) selection relative to the base category (full-time students). Therefore, the  $\gamma_j$  coefficients estimated from Equation (3) capture the effect of each type of pre-graduation work experience on the outcome of interest, after partialling out selection effects based on unobservable traits.

Assuming that the latent factors follow a standard normal distribution, the estimation of this joint model can be carried out through maximum simulated likelihood. To achieve identification without relying only on distributional assumption, we include an instrumental variable in the multinomial equation ( $Z_m$ ). The instrument has to be a strong predictor of working choices before graduation and—conditional on the set of explanatory variables included in Equation (3)—has to be uncorrelated with unobserved determinants of labour market outcomes.

Several related papers exploited local/regional unemployment rate as instrument for working conditions before degree completion under the assumption that labour market conditions at the time of taking the decision to work do not affect the final outcome directly (see, among others, Hakkinen (2006) and Triventi (2014)). In this paper we adopt a similar strategy, since we also exploit variation at the local level (i.e. the municipality of residence during the degree) to achieve identification. However, instead of using the unemployment rate, we constructed another measure to proxy for local labour market opportunities. This variable consists in the percentage of registered employment contracts over working age population (in a given year) within a radius of 30 km surrounding the student's municipality of residence two years before the graduation year. This measure allows us to capture employment potential at the very local level, without constraining the area capturing local labour markets to be defined only on the basis of administrative borders (i.e. municipality, province or regions), as done in previous papers on this issue. In particular, the instrument has been constructed as follows. We have first retrieved administrative information about the number of newly registered employment contracts for each municipality of Catalonia during a specific year [11]. Second, we have collected data on working age population from the administrative register of inhabitants at the municipality level. Finally, for each year we have

computed the ratio between the total number of registered contracts and the number of working age individuals of all municipalities within a radius of 30 km from the municipality of residence of the individuals [12]. This variable represents a proxy for (potential) local labour market opportunities in a given period. Since we aim at predicting working activities two years before graduation, we imputed our measure of employment potential to each graduation cohort according to the population-weighted average from the two years preceding the graduation (e.g. 2011 and 2012 for those graduated in 2013 and interviewed in 2017). The spatial distribution of our proxy for employment potential is displayed in Figure 1, separately for the three periods 2005–2006, 2008–2009 and 2011–2012 (which are imputed to waves 2011, 2014 and 2017 respectively) and represents the instrumental variable used as predictor of work activities before graduation ( $Z_m$ ). As long as the instrument varies at the municipality level, we cluster standard errors accordingly.

As previously observed, employment potential before graduation can be considered a valid instrument if it has a strong predicting power to explain the probability of having a given kind of job while studying, but does not affect directly labour market outcomes. The first condition is likely to hold, since the probability of working while studying is influenced by local labour market conditions and the existence of such relationship can be directly inferred from the data. The second condition represents an identifying assumption. The validity of the use of local employment potential as valid instrument might be questioned in case of persistency in local labour market conditions over time, which could affect labour market status four years after graduation (Oreopoulos *et al.*, 2012). However, there are reasons to consider that this issue is not likely to be a serious concern in this case. First, we impute employment potential according to the information from two years before graduation, while labour market outcomes are observed four years after graduation, implying a six-year lag with respect to the measurement of local labour market conditions. Second, we considered the information regarding the municipality of residence before graduation, but the completion of the university degree tends to increase geographical mobility (e.g. Haapanen and Böckerman, 2017), which might break the link with post-graduation employment potential and pre-graduation local labour market conditions. Third, the inclusion of university indicators and a large set of field of study fixed effects should capture most of the unobserved heterogeneity (due to family or local unobservables) that might create a direct correlation between our measure of employment and the residuals of the outcome equation(s). Nevertheless, in order to provide evidence in favour of the validity of the underlying hypothesis and to discard the possibility that the instrument (local employment potential before graduation) is in part capturing current local labour market conditions, we run two different robustness checks. First, we take advantage of the non-linear structure of the mixed multinomial model, which makes the structural equation identified even without any instrument, and include the measure of employment potential in the outcome equation(s) to test for the significance of the corresponding coefficient(s). Finding significant estimates would indicate that the variable used as instrument has a direct effect on the outcome, violating the exclusion restriction hypothesis. Second, we re-estimate the model including as additional control an alternative proxy for “current” local labour market conditions (i.e. in the year of the survey). Specifically, exploiting information about the number of individuals registered as unemployed in each municipality, we constructed a proxy for local unemployment by taking the ratio with respect to the adult population (information about the active population at the municipality level is not available). As long as the information about registered unemployment is also separately available for individuals in the 16–24 age range, we also computed the same variable to capture youth unemployment in the local area. This proxy of local unemployment rate should capture current local economic conditions. Therefore, if our instrument is strongly correlated with current labour market conditions, we should observe important changes in the estimates of interest when controlling for local

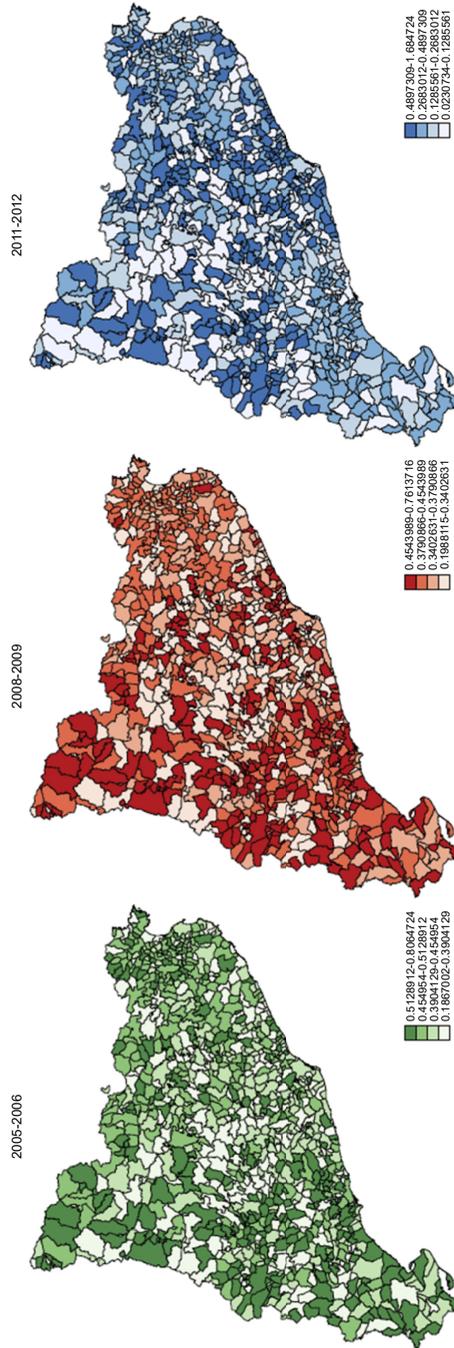


Figure 1. Employment potential measure by wave

unemployment rate in the survey year. Moreover, as long as endogenous mobility of university graduates, related to local economic conditions, could also represent a source of bias, we also checked the results obtained after retaining only the individuals who remained in the same province after graduation (i.e. the stayers).

## 5. Results

### 5.1 OLS estimates

Table 3 shows the OLS estimates of the impact of combining working activities with university education on post-graduation labour market performance. As for the probability of being employed 4 years after graduation (column (1)), this is generally higher for those who have worked during tertiary education. The highest estimated differentials are associated with jobs related to the field of education (+3.1 percentage points (pp) and +4.8 pp for part-time and full-time respectively). The employment “premium” for working while studying is lower for those working in jobs not related to the field of education: +2.3 pp and +1.2 pp for part-time and full-time jobs respectively, with the latter insignificantly different with respect to full-time students. When considering the probability of getting a permanent contract (column (1) of Table 3) the picture slightly changes, since work intensity appears to be more relevant than job-field match for the chances of being in a stable job position. In fact, for those who have worked full-time the probability of having a permanent contract 4 years after graduation is higher by 9.2 pp and 9 pp (for jobs related and not related to the field of education respectively) with respect to full-time students, while for those working part-time these premiums are of 5.5 pp for jobs related to the field of education and 6 pp for not related jobs. Finally, considering the match between the job 4 years after graduation and the specific degree obtained, graduates who have worked in jobs not related to their field of education

Outcome	Employed	Permanent contract	Specific degree required
Full-time student	<i>Reference category</i>		
Part-time job – related	0.031*** (0.005)	0.055*** (0.008)	0.041*** (0.008)
Part-time job – not related	0.023*** (0.006)	0.060*** (0.009)	–0.039*** (0.009)
Full-time job – related	0.048*** (0.007)	0.092*** (0.011)	0.032*** (0.011)
Full-time job – not related	0.012 (0.012)	0.090*** (0.018)	–0.140*** (0.017)
Male	0.000 (0.005)	–0.017** (0.008)	–0.006 (0.007)
Age	–0.003*** (0.001)	0.010*** (0.002)	–0.014*** (0.002)
Highest parental education = primary or less	<i>Reference category</i>		
Highest parental education = secondary	0.008 (0.005)	–0.010 (0.008)	0.008 (0.008)
Highest parental education = tertiary	0.004 (0.005)	–0.029*** (0.008)	0.009 (0.008)
R squared	0.032	0.122	0.126
Number of observations	24,704	21,870	21,883

**Note(s):** Robust standard errors in parenthesis; \*\*\* significant at 1%, \*\* significant at 5%, \* significant at 10%. All regressions include dummies for wave and university, as well as field of study fixed effects (96 indicators)

**Table 3.**  
OLS results

have a significantly lower probability to end up in occupations that match their specific degree (−3.9 pp and −14 pp for part-time and full-time jobs respectively), relative to their full-time student counterparts. On the contrary, individuals who have worked in occupations that match their field of education have a higher probability, with respect to full-time students, to end up in jobs that require their specific degree (+4.1 pp and +3.2 pp for part-time and full-time jobs respectively).

### 5.2 Multinomial endogenous treatment model estimates

The results obtained by OLS suggest that working before graduation in jobs related to the field of education, particularly full-time, is crucial in order to better perform in the labour market at the early stage of the working career. However, these estimates might be biased due to the presence of unobserved factors that might simultaneously affect the probability of working while studying and labour market performance. In order to control for this possible self-selection into working activities, we estimate multinomial endogenous treatment models that allow controlling for latent factors in order to properly identify the impact of working while studying on future labour market outcomes. As explained in Section 4, we use as instrumental variable the number of registered contracts over working age population for all municipalities within a radius of 30 km from the municipality of residence of the individuals, during the two years before the graduation [13]. We report the estimates from the multinomial selection equation (Equation 2), expressed as average marginal effects in Table A1 in Appendix. It is possible to see that in general our employment potential measure has a significant effect on employment decisions before graduation, thus confirming the validity of the elicited variable for predicting the endogenous working condition variable. Specifically, a unitary increase in local employment potential reduces the probability of being a full-time student by 13.7 pp, and increases the propensity to work (especially in part-time jobs unrelated to the field of study −5.6 pp, and in full-time jobs related to the field of study −4.1 pp). We also carried out a likelihood ratio test for the joint significance of the coefficients of employment potential in the multinomial equations, which is equal to 23.6 ( $p$ -value = 0.0001), pointing out that the instrument is not weak.

Table 4 shows selected estimates from the final outcome of the multinomial endogenous treatment model (Equation 3). First of all, the multinomial endogenous treatment model confirms the results obtained by OLS, which highlights the importance of working in a job that matches the field of study to enjoy higher chances of being employed after graduation [14]. After ruling out self-selection, the employment premium for having worked in a job related to the field of study is 6.3 and 5.2 pp for part-time and full-time jobs, respectively, which are slightly higher than the corresponding OLS estimates. This is indeed due to the presence of a (modest) negative selection, as shown by the  $\lambda$  coefficients associated to these two working conditions, indicating that individuals who are more likely to self-select into jobs related to the degree before graduation based on their unobservable traits are less likely to be employed after completing the degree. The estimated difference in employment probability between students who worked full-time in a job unrelated to the field of education and full-time student is again not significant, whereas, after having taken into account selection, working in a part-time job mismatched with the field of education turns out to decrease the chances to be employed.

Considering the probability of ending up with a permanent contract, our selectivity-corrected estimates confirm that having worked before graduation has generally a positive effect on the chances of getting a permanent contract four years after completing university. Nonetheless, the difference in the probability of having a stable position relative to those who never worked before graduation is stronger for jobs related to the field of study.

Finally, the evidence regarding post-graduation job-qualification match obtained from the joint multinomial selection model is in line with previous OLS estimates, as for what concerns the detrimental effect of pre-graduation job experiences unrelated to the field of study on post-

Outcome	Employed	Permanent contract	Specific degree required
Full-time student	<i>Reference category</i>		
Part-time job – related	0.063*** (0.011)	0.296*** (0.034)	0.060 (0.068)
Part-time job – not related	-0.204*** (0.010)	0.165*** (0.038)	-0.423*** (0.030)
Full-time job – related	0.052*** (0.008)	0.230*** (0.077)	0.026 (0.032)
Full-time job – not related	0.010 (0.012)	-0.006 (0.152)	-0.155*** (0.034)
$\lambda_2$	-0.050*** (0.007)	-0.278*** (0.037)	-0.038 (0.082)
$\lambda_3$	0.273*** (0.007)	-0.111*** (0.041)	0.453*** (0.034)
$\lambda_4$	-0.016** (0.008)	-0.146* (0.086)	-0.003 (0.027)
$\lambda_5$	-0.006 (0.009)	0.114 (0.163)	-0.003 (0.023)
Number of observations	24,704	21,870	21,883

**Note(s):** Standard errors (in parenthesis) are clustered at the municipality level; \*\*\* significant at 1%, \*\* significant at 5%, \* significant at 10%. All regressions include controls for gender, age (in the survey year for the outcome equation, two years before graduation in the multinomial equation), highest parental education, dummies for wave and university, as well as field of study fixed effects (96 indicators for the outcome equations, 17 for the multinomial equation)

**Table 4.**  
Multinomial  
endogenous treatments  
(selected coefficients)

graduation job match. These effects are higher than the corresponding OLS estimates, especially for part-time unrelated jobs, due to the strong positive selection into this kind of work activity due to unobservable characteristics. This means that those who are more inclined to get an unrelated job before graduation due to their unobservable characteristics are more likely to be in the same status after graduation as well. As for the estimates attached to part-time and full-time pre-graduation jobs related to the field of study, these are both positive, but not precisely estimated [15].

On the whole, these results point to the following findings. First of all, in order to properly gauge the impact of working while studying on future employment performance, it is crucial to take into account not only work intensity, but also the relationship between the job and the field of education. In fact, part-time and full-time pre-graduation work experiences show different payoffs after graduation according to their match with the degree's contents. Second, our findings reveal that, overall, what really matters is having a pre-graduation job that matches the field of study. In fact, those who have worked in occupations related to their studies have generally better post-graduation labour market outcomes than their counterparts who have studied full-time. The former are also more likely to be employed after graduation than individuals working in occupations unrelated to their field of study and have better chances of having a job that matches their specific degree. Even job stability is more positively affected by work experiences related to the contents of bachelor studies. Third, self-selection matters and must be taken into account in order to obtain a reliable and clear picture about the effects of working while studying on subsequent labour market outcomes. In fact, the unobservable characteristics that affect the propensity to combine working activities with university education are, in most cases, also related to post-graduation employability and job quality.

## 6. Conclusions

This paper investigated the relationship between work activities carried out before completing the university degree and their subsequent labour market performance. Pre-graduation jobs are classified according to two relevant dimensions: work intensity (part-time and full-time) and the relationship with the field of study.

We take into account endogenous self-selection into each type of pre-graduation jobs, using a multinomial endogenous treatment model that exploits a measure of local employment potential as identifying variable. The results indicate that the probability of being employed four years after graduation is higher for graduates who have been working in occupations related to their field of study, regardless of work intensity, than for full-time students. At the same time, those working full-time in a job not related to the field of education show the same chances to be employed as full-time students, while part-time students turn out to be penalised. Also job intensity at the early stage of the career is clearly related to pre-graduation work experiences, since the chances of having a stable position increase for graduates who worked in jobs related to their field of study, while the likelihood of having a job that requires the specific degree obtained four years after graduation is significantly lower for those who worked in jobs unrelated to their studies before university completion [16].

Overall, these findings highlight the primary importance of working in jobs related to the field of education while enrolled in higher education in order to improve graduates' career success. This is consistent with the experimental evidence recently reported by [Van Belle et al. \(2020\)](#), indicating that only pre-graduation jobs related to the degree's content generate positive signals of better skills and trainability to the employers' eyes. Therefore, our results support the need to promote pre-graduation employment in activities that are matched to the degree's content, such as compulsory internship programmes (in line with [Baert et al., 2021](#)). Moreover, the empirical analysis highlights the relevance of jointly considering different dimensions of pre-graduation working activities to understand whether and to what extent they affect future employability and job quality, since not every kind of work activity pays off in the graduates' labour market. Finally, our work emphasises the need to account for self-selection based on unobservable traits, in order to properly appreciate the costs and benefits of combining study and work for graduates' labour market outcomes.

## Notes

1. However, working while studying, especially in jobs unrelated to the university degree, could represent a (negative) signal to the employers, reflecting students' and families' liquidity constraints, which might generate discrimination against students from less-advantaged social backgrounds. See [Baert et al. \(2016\)](#) for a comprehensive explanation of theoretical models that could be useful to understand the mechanisms through which pre-graduation work can affect future labour market outcomes.
2. See footnote 4 in the related literature section.
3. As explained below, the latter works based on survey data face an important problem of endogeneity, since student work is a choice variable that depends on students' unobservable traits, potentially related to future labour market outcomes (i.e. a self-selection issue).
4. In this paper, we focus on the labour market performance of graduates. However, it is important to mention other relevant studies concerning the effects of working while in school on academic outcomes, since this could be one of the mechanisms behind the effect on labour market outcomes. The general findings, obtained using different estimation approaches and identification strategies, point to a negative impact of pre-graduation working experiences on academic achievements in terms of both time to degree and score obtained ([Theune, 2015](#); [Darolia, 2014](#); [Triventi, 2014](#); [Body et al., 2014](#); [Avdic and Gartell, 2015](#); [Wenz and Yu, 2010](#); [Stinebrickner and Stinebrickner, 2014](#)). Nonetheless, the academic penalisation due to working while studying seems to depend on working time, as reported by [Triventi \(2014\)](#), [Darolia \(2014\)](#) and [Body et al. \(2014\)](#). See [Neyt et al. \(2019\)](#) for a recent and comprehensive review.

5. From the 2008 wave, private universities and on-line universities have been progressively incorporated in the survey. However, in this paper we focus only on graduates from public universities (which account for about 75% of the whole population of graduates), since not all the variables of interest are available for private and on-line universities and because these universities are fully covered only from the 2014 wave of the survey. Moreover, foreigners who graduated from Catalan universities are only covered in the last wave of the survey (2017) and represent less than 4% of the observations of this wave. Notice also that for public universities, the response rate in the last three waves is around 55%, with a sampling error of about 0.6%. Notice also that survey participants are selected from successive cohorts of bachelor graduates, but some of them might have enrolled in a master degree or in a PhD in subsequent years. More information about the AQU survey can be found at: <https://www.aqu.cat/en/Studies/Surveys-and-thematic-studies/Labour-market>.
6. It is worth mentioning that the survey does not distinguish internships from other type of pre-graduation jobs. Nonetheless, given the purpose of internship programs, they can be reasonably assimilated to the group of jobs (part time/full time) related to the field of study.
7. Other situations include the graduates in the survey who declare to be self-employed (8.5%), internship work (4.9%) or irregular employment (0.75%).
8. Dynamic discrete choice models that account for the endogenous nature of the choice to work while studying have also been more recently applied by [Baert et al. \(2022\)](#), to estimate the employment effects of working during secondary education.
9. Field of study fixed effects enable providing within-field differences in the outcome by pre-graduation working status, and this should reduce possible selection issues due to the choice of the degree and its possible interaction with the decision to work. We control for very detailed fixed effects in the outcome equation (96 categories), which are grouped into 17 majors in the multinomial equation to reduce the curse of dimensionality (as displayed in [Tables 1 and 2](#)).
10. The parameters associated with the latent factors in the multinomial choice equation are normalised as  $\delta_j = 1$  for every option  $j$ , as in standard multinomial logit models.
11. This information is available on a monthly basis since 2005 on the webpage of the Spanish Employment Bureau: <https://www.sepe.es/HomeSepe/que-es-el-sepe/estadisticas/datos-estadisticos/municipios.html>.
12. We also computed employment potential using different radii to test for robustness, see [Section 5.2](#).
13. We have also adopted other radii to compute the measure of employment potential such as 20 km or 40 km, getting very similar results. These estimates are shown in [Table A2](#) in [Appendix](#).
14. As stressed in [Section 4](#), we carry out two estimates to corroborate the validity of the instrument. Specifically, we run the baseline estimates including employment potential as a control variable, in order to test whether this has a direct effect on the outcome equation, which would be a sign of violation of the exclusion restriction. [Table A3](#) in [Appendix](#) show that the coefficients related to employment potential are not statistically significant, thus reassuring us about the validity of the instrument. Moreover, in [Table A4](#) we show the baseline estimates with the inclusion of a proxy of current local unemployment rate, both for the whole population and for young (16–24) individuals, to alternatively test whether our instrument is capturing current local labour market conditions and thus directly affecting the outcomes. Results are unaffected by the inclusion of these additional controls, thus further corroborating the validity of the chosen instrument.
15. As mentioned above, it could be argued that selective location choices might represent a driver of our results. Unfortunately, our data do not provide specific information about mobility of students after graduation across municipalities. Nonetheless, there is  $e$  information about the current place of work classified as follows: (1) Barcelona, (2) Girona, (3) Lleida, (4) Tarragona, (5) Rest of Spain, (6) European Union, (7) Rest of the World. Hence, we looked at the percentage of students changing location between the period while they were enrolled at the university and the year of the survey. The rate of mobility is not that low, since around 17% of students changed place of residence. Most of these movements concern students who moved to Barcelona after graduation (7%). As a robustness check, we replicated the estimates by retaining only the individuals who remained in the

same Catalan province where they resided while studying the degree. Results are consistent with those using the entire sample information, which indicates that selective location choices are unlikely to be a relevant driver of the results. These estimates are available upon request.

16. As noticed by an anonymous referee, an important contribution of this work could be to explicitly analyse the heterogeneity of the impacts by areas of study. Unfortunately, due to the limited number of observations by broad areas that generates estimation issues, we are not able to properly address this interesting aspect of the analysis. Hence, we leave this issue open for further research.

## References

- Altonji, J.G., Arcidiacono, P. and Maurel, A. (2016), "The analysis of field choice in college and graduate school: determinants and wage effects", *Handbook of the Economics of Education*, Vol. 5, pp. 305-396.
- Avdic, D. and Gartell, M. (2015), "Working while studying? Student aid design and socioeconomic achievement disparities in higher education", *Labour Economics*, Vol. 33, pp. 26-40.
- Baert, B.S., Neyt, B., Omey, E. and Verhaest, D. (2022), "Student work during secondary education, educational achievement, and later employment: a dynamic approach", *Empirical Economics*, pp. 1-31 (in press).
- Baert, S., Neyt, B., Siedler, T., Tobback, I. and Verhaest, D. (2021), "Student internships and employment opportunities after graduation: a field experiment", *Economics of Education Review*, Vol. 83, 102141.
- Baert, S., Rotsaert, O., Verhaest, D. and Omey, E. (2016), "Student employment and later labour market success: no evidence for higher employment chances", *Kyklos*, Vol. 69 No. 3, pp. 401-425.
- Body, K.M.D., Bonnal, L. and Giret, J.F. (2014), "Does student employment really impact achievement? The case of France", *Applied Economics*, Vol. 46 No. 25, pp. 3061-3073.
- Darolia, R. (2014), "Working (and studying) day and night: heterogenous effect of working on the academic performance of full-time and part-time students", *Economic of Education Review*, Vol. 38, pp. 38-50.
- Deb, P. and Trivedi, P.K. (2006), "Maximum simulated likelihood estimation of a negative binomial regression model with multinomial endogenous treatment", *Stata Journal*, Vol. 6 No. 2, pp. 246-255.
- Dolado, J.J., Jansen, M., Felgueroso, F., Fuentes, A. and Wölf, A. (2013), "Youth labour market performance in Spain and its determinants: a micro-level perspective", OECD Economics Department Working Papers, No. 1039, OECD Publishing.
- Geel, R. and Gellner, U.B. (2012), "Earning while learning: when and how student employment is beneficial", *Labour*, Vol. 26 No. 3, pp. 313-340.
- Haapanen, M. and Böckerman, P. (2017), "More educated, more mobile? Evidence from post-secondary education reform", *Spatial Economic Analysis*, Vol. 12 No. 1, pp. 8-26.
- Hakkinen, I. (2006), "Working while enrolled at university: does it pay?", *Labour Economics*, Vol. 13, pp. 167-189.
- Hotz, J.V., Xu, L.C., Tienda, M. and Ahituv, A. (2002), "Are there returns to the wages of young men from working while in school?", *The Review of Economics and Statistics*, Vol. 84 No. 2, pp. 221-236.
- Le Barbanchon, T., Ubfal, D. and Araya, F. (2020), "The effects of working while in school: evidence from Uruguayan lotteries", Discussion Paper 13929, IZA, Bonn.
- Margaryan, S., Saniter, N., Schumann, M. and Siedler, T. (2020), "Do internships pay off? The effects of student internships on earnings", *Journal of Human Resources*, 0418-9460R2.
- Molitor, C.J. and Leigh, D.E. (2005), "In-school work experience and the return to two-year and four-year colleges", *Economics of Education Review*, Vol. 24, pp. 459-468.
- Neyt, B., Omey, E., Verhaest, D. and Baert, S. (2019), "Does student work really affect educational outcomes? A review of the literature", *Journal of Economic Surveys*, Vol. 33 No. 3, pp. 896-921.

- Nunley, J.M., Pugh, A., Romero, N. and Seals, R.A. Jr (2016), "College major, internship experience, and employment opportunities: estimates from a résumé audit", *Labour Economics*, Vol. 38, pp. 37-46.
- Oreopoulos, P., von Wachter, T. and Heisz, A. (2012), "The short-and long-term career effects of graduating in a recession", *American Economic Journal: Applied Economics*, Vol. 4 No. 1, pp. 1-29.
- Passaretta, G. and Triventi, M. (2015), "Work experience during higher education and post-graduation occupational outcomes: a comparative study on four European countries", *International Journal of Comparative Economics*, Vol. 56, pp. 232-253.
- Pastore, F., Quintano, C. and Rocca, A. (2021), "Some young people have all the luck! The duration dependence of the school-to-work transition in Europe", *Labour Economics*. doi: [10.1016/j.labeco.2021.101982](https://doi.org/10.1016/j.labeco.2021.101982).
- Pastore, F., Quintano, C. and Rocca, A. (2022), "The duration of the school-to-work transition in Italy and in other European countries: a flexible baseline hazard interpretation", *The International Journal of Manpower*, Vol. ahead-of-print No. ahead-of-print. doi: [10.1108/IJM-03-2021-0135](https://doi.org/10.1108/IJM-03-2021-0135).
- Sanchez-Gelabert, A., Figueroa, M. and Elias, M. (2017), "Working whilst studying in higher education: the impact of the economic crisis on academic and labour market success", *European Journal of Education*, Vol. 52 No. 2, pp. 232-245.
- Stinebrickner, R. and Stinebrickner, T.R. (2014), "A major in science? Initial beliefs and final outcomes for college major and dropout", *The Review of Economic Studies*, Vol. 81 No. 1286, pp. 426-472.
- Theune, K. (2015), "The working status of students and time to degree at German universities", *Higher Education*, Vol. 70, pp. 725-752.
- Triventi, M. (2014), "Does working during higher education affect students' academic progression?", *Economics of Education Review*, Vol. 41, pp. 1-13.
- Van Belle, E., Caers, R., Cuypers, L., De Couck, M., Neyt, B., Van Borm, H. and Baert, S. (2020), "What do student jobs on graduate CVs signal to employers?", *Economics of Education Review*, Vol. 75, 101979.
- Weiss, F., Klein, M. and Grauenhorst, T. (2014), "The effects of work experience during higher education on labour market entry: learning by doing or an entry ticket?", *Work, Employment and Society*, Vol. 28 No. 5, pp. 788-807.
- Wenz, M. and Yu, W.C. (2010), "Term-time employment and the academic performance of undergraduates", *Journal of Education Finance*, Vol. 35 No. 4, pp. 358-373.

**Corresponding author**

Antonio Di Paolo can be contacted at: [antonio.dipaolo@ub.edu](mailto:antonio.dipaolo@ub.edu)

$\Delta$ Predicted probability	Full-time student	Part-time job related	Part-time job not related	Full-time job related	Full-time job not related
Employment potential ( $Z_m$ )	-0.137*** (0.029)	0.025 (0.024)	0.056** (0.023)	0.041** (0.019)	0.016 (0.012)
Male	0.050*** (0.007)	-0.017*** (0.006)	-0.033*** (0.006)	-0.003 (0.005)	0.002 (0.003)
Age two years before graduation	-0.047*** (0.001)	0.010*** (0.001)	0.006*** (0.002)	0.021*** (0.001)	0.010*** (0.000)
Highest parental education = primary or less			<i>Reference category</i>		
Highest parental education = secondary	0.017** (0.008)	0.015** (0.007)	-0.021*** (0.006)	-0.009* (0.005)	-0.003 (0.004)
Highest parental education = tertiary	0.042*** (0.007)	0.030*** (0.007)	-0.043*** (0.006)	-0.020*** (0.005)	-0.009** (0.004)
Wave 2011			<i>Reference category</i>		
Wave 2014	-0.013* (0.007)	0.047*** (0.007)	0.043*** (0.006)	-0.061*** (0.005)	-0.016*** (0.003)
Wave 2017	0.037*** (0.008)	-0.019*** (0.006)	0.082*** (0.006)	-0.087*** (0.005)	-0.013*** (0.003)
Field of study = humanities			<i>Reference category</i>		
Field of study = language	0.028 (0.019)	0.146*** (0.017)	-0.171*** (0.017)	0.013** (0.006)	-0.017** (0.007)
Field of study = art	0.102*** (0.026)	0.029 (0.032)	-0.091*** (0.035)	0.001 (0.009)	-0.040*** (0.008)
Field of study = business and economics	-0.060*** (0.020)	0.161*** (0.022)	-0.259*** (0.013)	0.190*** (0.007)	-0.032*** (0.006)
Field of study = law, sociology and political sciences	-0.032 (0.023)	0.058** (0.023)	-0.116*** (0.015)	0.074*** (0.007)	0.016** (0.007)
Field of study = communication and journalism	-0.039* (0.023)	0.194*** (0.022)	-0.195*** (0.016)	0.068*** (0.008)	-0.028*** (0.007)
Field of study = education	-0.031* (0.018)	0.189*** (0.018)	-0.202*** (0.015)	0.074*** (0.006)	-0.029*** (0.006)
Field of study = social work	-0.145*** (0.019)	0.153*** (0.019)	-0.122*** (0.021)	0.122*** (0.013)	-0.008 (0.009)
Field of study = biology, geology and environmental sciences	0.169*** (0.015)	-0.014 (0.019)	-0.150*** (0.015)	0.039*** (0.006)	-0.044*** (0.007)
Field of study = chemistry, physics, maths and statistics	0.128*** (0.016)	0.059*** (0.019)	-0.197*** (0.017)	0.048*** (0.010)	-0.039*** (0.006)
Field of study = health (excluding medicine)	-0.032 (0.027)	0.102*** (0.024)	-0.174*** (0.021)	0.147*** (0.015)	-0.042*** (0.008)
Field of study = psychology and related degrees	-0.002 (0.020)	0.053*** (0.019)	-0.082*** (0.017)	0.030*** (0.009)	0.002 (0.008)
Field of study = pharmacy, biomedicine and veterinary	0.138*** (0.037)	0.126*** (0.031)	-0.277*** (0.018)	0.066*** (0.010)	-0.053*** (0.006)
Field of study = architecture and construction	-0.006 (0.019)	0.221*** (0.024)	-0.269*** (0.018)	0.108*** (0.014)	-0.054*** (0.006)
Field of study = industrial, chemical and electronic engineering	0.011 (0.020)	0.151*** (0.024)	-0.251*** (0.017)	0.127*** (0.012)	-0.039*** (0.008)
Field of study = telecommunication and informatics	-0.044** (0.018)	0.247*** (0.024)	-0.276*** (0.015)	0.120*** (0.011)	-0.047*** (0.006)
Field of study = agricultural engineering and related	0.039 (0.025)	0.108*** (0.023)	-0.204*** (0.024)	0.087*** (0.012)	-0.030*** (0.010)
Number of observations			24,704		

**Note(s):** Standard errors (in parenthesis) are clustered at the municipality level; \*\*\* significant at 1%, \*\* significant at 5%, \* significant at 10%. The model also includes fixed effects for the university of graduation (coefficients are not reported in the table to accomplish with the rules of the contract for data transfer)

**Table A1.** Average marginal effects from mixed multinomial logit

**Table A2.**  
Multinomial  
endogenous treatment  
model using various  
radii to compute the  
measure of  
employment potential

	Employed	Permanent contract	Specific degree required	Employed	Permanent contract	Specific degree required	Employed	Permanent contract	Specific degree required
<i>Multinomial endogenous treatment estimates</i>									
Full-time student	0.063*** (0.011)	0.294*** (0.033)	0.060 (0.070)	0.063*** (0.011)	0.296*** (0.034)	0.060 (0.068)	0.060*** (0.008)	0.295*** (0.034)	0.060 (0.069)
Part-time job – related	-0.204*** (0.010)	0.169*** (0.039)	-0.423*** (0.031)	-0.204*** (0.010)	0.165*** (0.038)	-0.423*** (0.030)	-0.222*** (0.009)	0.168*** (0.039)	-0.423*** (0.030)
Part-time job – not related	0.052*** (0.008)	0.232*** (0.080)	0.027 (0.034)	0.052*** (0.008)	0.230*** (0.077)	0.026 (0.032)	0.049*** (0.007)	0.229*** (0.075)	0.026 (0.033)
Full-time job – related	0.010 (0.012)	-0.004 (0.154)	-0.155*** (0.036)	0.010 (0.012)	-0.006 (0.152)	-0.153*** (0.034)	0.012 (0.012)	-0.006 (0.151)	-0.153*** (0.035)
Full-time job – not related	-0.059*** (0.007)	-0.276*** (0.036)	-0.038 (0.084)	-0.050*** (0.007)	-0.278*** (0.037)	-0.038 (0.082)	-0.050*** (0.006)	-0.277*** (0.037)	-0.038 (0.083)
$\lambda_2$	0.273*** (0.007)	-0.115*** (0.042)	0.453*** (0.035)	0.273*** (0.007)	-0.111*** (0.041)	0.453*** (0.034)	0.295*** (0.005)	-0.115*** (0.042)	0.453*** (0.035)
$\lambda_3$	-0.016** (0.008)	-0.148* (0.089)	-0.003 (0.028)	-0.016** (0.008)	-0.146* (0.086)	-0.003 (0.027)	-0.013* (0.007)	-0.145* (0.084)	-0.003 (0.027)
$\lambda_4$	-0.006 (0.009)	0.113 (0.165)	-0.003 (0.024)	-0.006 (0.009)	0.114 (0.163)	-0.003 (0.023)	-0.013** (0.005)	0.115 (0.162)	-0.003 (0.024)
$\lambda_5$									
<i>Mixed multinomial logit estimates for the exclusion restriction: employment potential (<math>Z_{it}</math>)</i>									
Part-time related vs full time student	0.319* (0.164)	0.417*** (0.155)	0.398** (0.160)	0.558*** (0.166)	0.659*** (0.173)	0.631*** (0.182)	0.697*** (0.177)	0.784*** (0.183)	0.761*** (0.197)
Part-time not related vs full time student	0.619*** (0.159)	0.703*** (0.187)	0.599*** (0.176)	0.769*** (0.185)	0.839*** (0.215)	0.782*** (0.203)	0.799*** (0.202)	0.880*** (0.236)	0.783*** (0.219)
Full time related vs full time student	0.814*** (0.220)	0.876*** (0.206)	0.870*** (0.211)	0.910*** (0.246)	1.062*** (0.244)	1.045*** (0.273)	1.015*** (0.279)	1.202*** (0.279)	1.183*** (0.287)
Full time not related vs full time student	0.493 (0.305)	0.614* (0.343)	0.652* (0.346)	0.894** (0.389)	0.940** (0.439)	0.960** (0.436)	0.802* (0.461)	0.812 (0.516)	0.888* (0.515)
Number of observations	24,704	21,870	21,883	24,704	21,870	21,883	24,704	21,870	21,883
<i>Goodness of fit from multinomial logit</i>									
McFadden		0.080			0.080			0.080	
AIC		65107.403			65104.899			65107.790	
BIC		66081.169			66078.666			66081.556	

**Note(s):** Standard errors (in parenthesis) are clustered at the municipality level; \*\*\* significant at 1%, \*\* significant at 5%, \* significant at 10%. All regressions include controls for gender, age (in the survey year for the outcome equation, two years before graduation in the multinomial equation), highest parental education, dummies for wave and university, as well as field of study fixed effects (96 indicators for the outcome equations, 17 for the multinomial equation)

Outcome	Employed	Permanent contract	Specific degree required
<i>Mixed multinomial logit estimates for employment potential (<math>Z_m</math>)</i>			
Part-time job related vs full-time student	0.564*** (0.166)	0.622*** (0.180)	0.628*** (0.180)
Part-time job related vs full-time student	0.737*** (0.197)	0.826*** (0.215)	0.821*** (0.217)
Part-time job not related vs full-time student	0.912*** (0.246)	1.039*** (0.244)	1.045*** (0.248)
Full-time job not related vs full-time student	0.894** (0.389)	0.975** (0.435)	0.960** (0.437)
<i>Outcome equations from the multinomial endogenous treatment model</i>			
Full-time student		<i>reference category</i>	
Part-time job – related	0.063*** (0.011)	0.296*** (0.034)	0.060 (0.068)
Part-time job – not related	-0.204*** (0.010)	0.165*** (0.038)	-0.423*** (0.030)
Full-time job – related	0.052*** (0.008)	0.230*** (0.077)	0.026 (0.032)
Full-time job – not related	0.010 (0.012)	-0.006 (0.152)	-0.155*** (0.034)
Employment potential ( $Z_m$ )	-0.013 (0.015)	0.037 (0.024)	0.020 (0.025)
$\lambda_2$	-0.050*** (0.007)	-0.177*** (0.031)	-0.037 (0.077)
$\lambda_3$	0.273*** (0.007)	0.043 (0.033)	0.453*** (0.032)
$\lambda_4$	-0.016** (0.008)	-0.320*** (0.022)	-0.002 (0.024)
$\lambda_5$	-0.006 (0.009)	0.051 (0.048)	-0.003 (0.022)
Number of observations	24,704	21,870	21,883

**Table A3.** Multinomial endogenous treatment model, controlling for employment potential in the outcome equation

**Note(s):** Standard errors (in parenthesis) are clustered at the municipality level; \*\*\* significant at 1%, \*\* significant at 5%, \* significant at 10%. All regressions include controls for gender, age (in the survey year for the outcome equation, two years before graduation in the multinomial equation), highest parental education, dummies for wave and university, as well as field of study fixed effects (96 indicators for the outcome equations, 17 for the multinomial equation)

Outcome	Registered local unemployment rate for			Young individuals (16–24)		
	Employed	Permanent contract	Specific degree required	Employed	Permanent contract	Specific degree required
Full-time student		<i>Reference category</i>			<i>Reference category</i>	
Part-time job – related	0.063*** (0.011)	0.212*** (0.028)	0.060 (0.068)	0.063*** (0.011)	0.211*** (0.029)	0.059 (0.061)
Part-time job – not related	-0.204*** (0.010)	0.037 (0.029)	-0.422*** (0.029)	-0.204*** (0.010)	0.042 (0.031)	-0.423*** (0.026)
Full-time job – related	0.052*** (0.008)	0.377*** (0.021)	0.026 (0.032)	0.052*** (0.008)	0.377*** (0.021)	0.026 (0.028)
Full-time job – not related	0.010 (0.012)	0.051 (0.046)	-0.154*** (0.034)	0.010 (0.012)	0.051 (0.047)	-0.157*** (0.030)
Local unemployment rate in survey year	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.015 (0.029)	-0.057 (0.046)	0.083* (0.049)
$\lambda_2$	-0.050*** (0.007)	-0.177*** (0.032)	-0.039 (0.081)	-0.050*** (0.007)	-0.177*** (0.033)	-0.033 (0.064)
$\lambda_3$	0.273*** (0.007)	0.038 (0.034)	0.452*** (0.034)	0.273*** (0.007)	0.034 (0.035)	0.455*** (0.026)
$\lambda_4$	-0.016** (0.008)	-0.321*** (0.022)	-0.003 (0.027)	-0.016** (0.008)	-0.320*** (0.022)	-0.001 (0.018)
$\lambda_5$	-0.006 (0.009)	0.050 (0.049)	-0.003 (0.023)	-0.006 (0.009)	0.051 (0.050)	0.001 (0.016)
Number of observations	24,704	21,870	21,883	24,704	21,870	21,883

**Note(s):** Standard errors (in parenthesis) are clustered at the municipality level; \*\*\* significant at 1%, \*\* significant at 5%, \* significant at 10%. All regressions include controls for gender, age (in the survey year for the outcome equation, two years before graduation in the multinomial equation), highest parental education, dummies for wave and university, as well as field of study fixed effects (96 indicators for the outcome equations, 17 for the multinomial equation). Registered local unemployment rate represents the number of individuals registered as unemployment in all municipalities located within a radius of 30 km over the corresponding population of reference

**Table A4.** Multinomial endogenous treatment model, controlling for registered local unemployment rate