University graduates' job-education mismatches in the Spanish labour market

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ABSTRACT

This paper focuses on educational mismatches in the Spanish labour market for recent university graduates. We analyse both horizontal mismatch and vertical mismatch, more specifically overqualification, considering subjective and objective indicators. The data used is the Labour Insertion Survey for Recent University Graduates, conducted by INE in 2014 and 2019. We analyse the determinants of mismatch at the first job after graduation and at the time of the interview, four years later. We also study the persistence of mismatches and the effect of the economic recession that started in 2008. Our results show the heterogeneity of mismatches across education fields. Individual characteristics, skills, study-related variables and job characteristics also determine the mismatch probability. We also find that graduates in 2014 not only experienced a lower probability of job-education mismatch than those graduated in 2010, but also the persistence was lower, so they had more chances of leaving out the mismatch

JEL-Classification: I21, J24, C25

Keywords: job-education mismatch; college education; discrete choice models; sample selection.

1. Introduction

The increase in the labour force education, worldwide competition or ageing population among other relevant socioeconomic changes has caused the appearance of educational mismatches in the labour market over the last decades (Flisi et al., 2017). Although this phenomenon has been studied since the 70s by Freeman (1976) and Thurow (1975) in the context of the United States economy, it is still present in nowadays labour markets. For instance, in 2019 the European Union presented a 21,9% of overqualified individuals with tertiary education from 20 to 64 years old (Eurostat), which demonstrates that there is still a need to understand this issue, especially for the Spanish case, where this percentage amounted 36,6% in 2019.

The aim of our research work is to study educational mismatches in the Spanish labour market for recent university graduates. Job-education mismatches can be differentiated in two types: vertical mismatches and horizontal or field-of-study mismatches. Following International Labour Organization definitions, a mismatch is vertical when the level of qualification of an individual is higher or lower than required. However, a mismatch is horizontal when the type or field of education is different from the one required. Within vertical mismatches we can distinguish between overqualification and underqualification.

In particular, the objective of this project is threefold. First, we will analyse the determinants of being educational mismatched (vertically and horizontally). For vertical mismatches, we will focus on overqualification, defining it using a subjective (self-perceived) indicator, although we will also explore an objective indicator based on occupation. Second, we will examine the persistence of overqualification and horizontal mismatches, comparing individuals' situation in the first job after graduating and their job four years later. We will also analyse which factors determine the probability of leaving a situation of job-education mismatch. Finally, we will study the impact of the 2008 Great Recession on overqualification and horizontal mismatches in Spain.

Looking at European data of overqualified workers between 20 and 64 years old with tertiary education in 2019, we can observe why the Spanish case is so noteworthy. Spain has a 36,6% of overqualified individuals, the highest value of the EU-28 sample (Eurostat). This seems especially relevant since other similar economies present significantly lower values, which is the case for Italy (20,2%), Portugal (14,8%) or even the EU-28 as a whole (21,9%). The Spanish case is even more worrisome if we look at the proportion of people between 25 and 54 years old with tertiary education in 2019, since Spain has a 42,3%, while the UE-28 percentage is of 34,6%, or even worse if we compare it with Portugal (30,1%) or Italy (22,0%) (Eurostat). Therefore, Spain produces more tertiary educated people than other European countries, which may increase its already significant overqualification problem, which implies an important underuse of human capital.

Moreover, the focus on recent graduates is important insofar as there is evidence that the risk of overqualification is higher among the youths (24-29 years old) compared to older ones (25-65 years old)

(Sicherman, 1991; Groot, 1996; Vahey, 2000; Cedefop, 2015). This encourages our focus on recent graduates and the need to study the persistence of job-education mismatches. For instance, in the Spanish case, Ramos (2017) states that for 2010 university graduates, 38% were overqualified in their first job after leaving university, while only 25,2% were so 4 years after leaving the university.

Finally, as the Spanish labour market reaction to the 2008 crisis was very strong, passing from an 8.2% unemployment rate in 2007 to a 26,1% in 2013 (Eurostat), we are also interested in capturing the effects of the recession on overqualification and horizontal mismatches. It is likely that the high unemployment rates experienced by the Spanish economy during the economic recession have forced university graduates to accept jobs that do not match their qualifications attainments. For instance, Cedefop (2015) states that the probability of overqualification in the EU-28 suffered a severe increase in the 2008-2014 period, attaining levels of 28%, compared with the 2001-2007 period, where it rounded the 17%.

This research will then offer a wide view of university graduates' job-education mismatches in the Spanish labour market, where evidence shows they represent an important problem. Therefore, to fulfil the three main purposes of our project, we will employ econometric techniques using microdata obtained from the Labour Insertion Survey for Recent University Graduates (EILU) in Spain, performed by the National Statistics Institute (INE) for years 2014 and 2019.

The rest of the paper is organized as follows. In Section 2 we review the most relevant literature on job-education mismatches. Section 3 presents and describes the data used in this work. In Section 4 we present the methodology and in section 5 the results obtained. Finally, Section 6 offers some concluding remarks as well as some lines of further research.

2. Literature review

Job-education mismatches have been widely studied in the Labour and Education Economics literature, especially for developed countries. Therefore, the first works regarding this issue were performed in the context of the United States, by Freeman (1976) and Thurow (1975). Nowadays, most of the existing literature is composed of empirical works that analyse the effect of job-education mismatches on wages or well-being (Verhaest et al. 2017). Moreover, while the former papers mostly focused on the analysis of vertical mismatches (Groot and Maassen van den Brink, 2000; McGuinness, 2006), recent studies have also paid attention to horizontal mismatch (Wolbers, 2003; Robst, 2007; Kim et. al, 2012; Verhaest et. al, 2013; Montt, 2017). Other contributions such as the literature review on overeducation done by Leuven and Oosterbeek (2011) are key to understand the existing literature on this field.

An important aspect of our study is to know the determinants of both overqualification and horizontal mismatches. Although most of the existing literature on this subject focus on overqualification determinants; Erdsiek (2017), Battu, et al. (1999); Verhaest and Omey (2010), Brunello and Cappellari

(2008) or Kucel and Byrne (2008), we have also found excellent works regarding the analysis of horizontal mismatches determinants, such as Wolbers (2003), Robst (2007) or the comprehensive literature review done in Somers et. al (2019). A general pattern between most of the existing literature can be established, since they generally state that both types of job-education mismatches are more likely for the following cases: Humanities and Arts or Social Sciences graduates, individuals with a temporary contract and graduates of public institutions. Many other factors such as the family background (Erdsiek, 2016) or the role of gender are also frequently studied in the literature, however, the results are not always homogenous, mainly due to the different datasets and type of measures used (Verhaest and Omey, 2010).

Focusing in the Spanish case, Alba-Ramirez (1993) was the first study on overqualification, where the author concluded that overqualified individuals tend to be young individuals, highly educated and with less experience. More recent studies as Albert and Davia (2018) obtained very interesting results regarding the study of job-education mismatches for recent graduates in Spain. They studied the mismatches from three different perspectives: vertical, horizontal and skill or knowledge mismatches. These authors, as well as Flores (2020), obtain no differences between gender in the probability of being mismatched in the first job after graduation in Spain, in line with other works for different countries such as Erdsiek (2017), Frei and Sousa-Poza (2012) or McGoldrick and Robst (1996). Results regarding gender are many times unclear (Montalvo, 2013 or Verhaest and Omey, 2010). Nevertherless, some authors defend the existence of significant differences across genders, for instance, Büchel and Battu(2003) or Erdsiek(2017) point out that women have higher risks of overqualification. Albert and Davia (2018) also analysed how the job search strategy could affect the probability of suffering a job-education mismatch. They got that using temporary work agencies, mass media or Internet, contacting with the employer or starting a business increase the probability of mismatch. Similar results are also obtained in previous research works (McGuinness et al., 2016; Blázquez and Mora, 2010; Carroll and Tani, 2015; Kucel and Byrne, 2008). Other relevant results of the latter authors describe that having good IT or English skills, having studied abroad, or receiving excellence or collaboration grants, which are related with high marks, reduce the probability of suffering overqualification. Additional recent studies focused on Spain, such as Flores (2020), Rodríguez-Esteban et al. (2019) or Albert, et al. (2019) obtain similar results in this respect.

Another relevant part of our study is the analysis of the persistence of job-education mismatches. Concerning this, we can distinguish some theories, such as the Occupational mobility theory (Rosen, 1972; Sicherman and Galor, 1990) or the Matching theory (Jovanovic, 1979), which consider overqualification as a temporary issue, while others believe it is a long-term problem, which is the case for the Assignment theory (Sattinger, 1993), the Job-screening theory (Spence, 1973) or the Job-competition theory (Thurow, 1975). Another well-known theory, the Spatial mobility theory (Büchel and Van Ham, 2003), has a mixed approach regarding the persistence of overqualification, since for these authors overqualification would last as long as workers cannot access to the global labour market or until local job markets improve their offer. Other alternative approaches to this issue may be inspired by the human capital theory (Becker, 1964), which suggests that overqualification might be persistent because observing human capital is impossible for employers, which leads to an imperfect information scenario. No theoretical models regarding horizontal mismatches have been found in the literature, which is also stated by Salas-Velasco (2021).

This debate regarding whether overqualification is a persistent or temporary issue is still part of the recent empirical literature, where we have found studies that suggest different results. For instance, following Frenette (2004) overqualification is persistent since Canadian graduates' overqualification results do not improve in the years after graduation, while Frei and Sousa-Poza (2012), who used a Swiss panel dataset, state that overqualification is a transitory phenomenon, since 90% of workers escaped overqualification in the next four years after being overqualified. However, despite the results obtained by Frei and Sousa-Poza (2012), most of the evidence, especially regarding recent university graduates, suggest that overqualification is a permanent problem. This is what Verhaest and Velden (2013) prove by analysing overqualification in the first five years of the career cycle of college graduates in 13 European countries and Japan. Their results showed that between graduates overqualified in their first job in 2000, 30% to 58% remained overqualified five years later. Another example of the evidence of persistence in overqualification could be what Meroni and Vera-Toscano (2017) obtained for graduates in fourteen European countries, using the 2005 REFLEX data.

Other studies, such as the one performed by Erdsiek (2017), examine overqualification dynamics over the early career of tertiary graduates in Germany, differentiating between raw state and true state dependence of previous overqualification. The latter considers the effect of individual heterogeneity when measuring the persistence of overqualification. Consequently, a true state dependence would imply that overqualification persistence arises from being overqualified in the previous period and not due to individual's characteristics. A similar study was previously performed by Blázquez and Budría (2012), using annual German data from 2000 to 2008. They found that 86% of overqualified individuals remained so the next year, while 2% of well-matched individuals entered overqualification. The difference between those rates is the already mentioned raw state dependence of overqualification. In this study, the authors found that only a 18% of the raw state dependence could be related to a true state dependence. Knowing whether overqualification is dependent on individual characteristics or on their own state in the previous period can be especially relevant for policy making.

The relatively scarce literature focused in Spain on overqualification (Alba-Ramírez and Blázquez, 2002; Congregado et al, 2016; Montalvo, 2013; Rivera Garrido, 2019) states that it seems to be a persistent phenomenon. This is also supported by Ramos (2017), who obtains in her study an incidence of 38% of overqualified graduates in their first job after leaving university and a 25,2% in their job four years after graduation. These results contrast with the ones found by former studies, such as Alba-Ramírez (1993), that suggest that overqualification may not be a persistent issue. We should also mention that although Rivera Garrido (2019) states the need of further studies to control for unobservable characteristics, we have not found any study of the Spanish scenario that considers this.

Another important aspect that arises in the analysis of job-education mismatches is the role of the economic performance. From a general perspective, Wolbers (2003) states that graduates who face an economic recession, which is the case for graduates in 2010 in Spain, are more likely to accept jobs which do not match their qualification. In line with the previous results, Cedefop (2015) states that the probability of being overqualified in the UE-28 rose from 17% for the pre-crisis graduates (2001-2007) to 28% for the period 2008-2014 graduates, implying a strong effect of the 2008-2014 recession period.

Regarding this issue in the Spanish context, Bartual-Figueras, et. al (2017) offer a descriptive analysis of overqualification in Catalonia. They find that overqualification increased significantly during the economic crisis period (2008-2014). Moreover, the authors were able to perform their analysis by industry sector, finding that the highest increase of overqualification was observed in sectors affected either by spending cuts or important activity decreases, such as the manufacturing industry. Regarding this aspect, our study will measure the effects of this recession by employing econometric techniques, which will offer a deeper analysis. We will also expand the analysis of Bartual-Figueras, et. al (2017) to the general Spanish context.

3. The data

The empirical analysis of this study is based on the Labour Insertion Survey for Recent University Graduates (EILU) in Spain, performed by the National Statistics Institute (INE). In this research work, we have used the two available waves of this survey, conducted in 2014 and 2019. The first wave includes a sample of 30,379 university graduates who finished their university degree in the 2009/2010 academic year, while the second one comprises 31,651 individuals who finished it in 2013/2014.

Individuals of the first wave were interviewed between September 2014 and February 2015, while for graduates of the second wave, the field work took place between July and December 2019. Contrary to what previous studies did (Albert and Davia, 2018) for the analysis of job-education mismatches using the 2014 wave, we have decided not to exclude graduates from the Bolonia system, since it was already implemented for the 2019 wave individuals.

This survey allows us to address all the objectives of our study. First, since it contains information for self-perceived job-education mismatches in the first job after graduation, as well as in the job occupied four years later, thus permitting to study the persistence of such mismatches. In this respect, we will explore which factors might have helped Spanish graduates to improve their mismatch situation 4 years after graduation. Second, the timing of the survey allows us to analyse whether the 2008 Great Recession has had an impact on the risk of job-education mismatches among Spanish university graduates.

There are other works in the literature that have used this survey, but only the 2014 wave (Flores, 2020; Rodríguez-Esteban et al. 2019; Albert et al., 2019; Albert and Davia, 2018). Up to our knowledge, our work is the first one using the 2014 and 2019 waves simultaneously. This has involved an important effort in harmonizing the data, as many of the variables have different names, definitions and/or measures in both waves. Using both waves imply an important refinement insofar as it allows us to compare a period of recession and expansion and, therefore, the implications of the business cycle in terms of job-education mismatches.

Apart from the main variables of interest in our analysis, i.e., those related to job-education vertical and horizontal mismatches, we also consider different groups of variables regarding individual characteristics, studies related variables, job characteristics and other social and economic characteristics (see Table 1 for a description of these variables).

Table 1. Variables definition

A. Job-education mismatches related variables

Variable	*Definition*
sp_first_overq	Self-perceived overqualification in first job (1 if the individual perceives overqualification, 0 otherwise)
sp_act_overq	Self-perceived overqualification in current job (1 if the individual perceives overqualification, 0 otherwise)
obj_first_overq	Overqualification in first job, objective indicator (1 if the individual is overqualified, 0 otherwise)
obj_act_overq	Overqualification in current job, objective indicator (1 if the individual is overqualified, 0 otherwise)
first_hmismatch	Self-perceived horizontal mismatch in first job (0: No mismatch; 1: Weak mismatch; 2: Strong mismatch)
act_hmismatch	Self-perceived horizontal mismatch in current job (0: No mismatch; 1: Weak mismatch; 2: Strong mismatch)
sp_out_overq	1 if the graduate was overqualified in the first job but no longer is in the current job (self-perceived indicator), 0 otherwise.
obj_out_overq	1 if the graduate was overqualified in the first job but no longer is in the current one (objective indicator), 0 otherwise.
improve_hmismatch	1 if the graduate improves his horizontal mismatch state from the first to the current job (going from a strong to a weak horizontal mismatch or directly getting out of the mismatch state), 0 otherwise.

B. Individual characteristics

Variable	*Definition*
male	1 if male, 0 otherwise
age	Different groups of age (under 30 years old, between 30 and 34 years old, 35 years old or older)
spanish	1 if Spanish, 0 otherwise
ict	ICT knowledge (Basic, Advanced, Expert)
lang2	1 if individual speaks two or more languages, 0 otherwise.
theor_sk	Theoretical knowledge (None, Low, Moderate, Good, Expert)
pract_sk	Practical skills (None, Low, Moderate, Good, Expert)
lang_sk	Language skills (None, Low, Moderate, Good, Expert)
it_sk	IT skills (None, Low, Moderate, Good, Expert)
soc_sk	Social skills (None, Low, Moderate, Good, Expert)
manag_sk	Management skills (None, Low, Moderate, Good, Expert)

Table 1. Variables definition (cont.)

C. Study related variables	
Variable	*Definition*
stud_abroad	1 if the graduate has studied abroad, 0 otherwise
grant_cv	1 if the graduate has obtained an excellence or collaboration grant during the degree, 0 otherwise
priv_univ	1 if university of origin is a private university, 0 if public
field_study	Field of study (Arts and Humanities, Social and Legal science, Science, Engineering and Architecture, Health sciences)
pract_out	1 if the graduate has done an internship outside the degree plan, 0 otherwise
postgrad	1 if the graduate has a postgraduate degree, 0 otherwise
D. Job and job-search related variables	
Variable	*Definition*
j_search(1-9)	Different methods of job search for the first job (nine binary variables for the different methods:1: Advertisments in Internet or Newspapers; 2: Using public or university employment service; 3: Using a temporary work agency; 4: Using personal contacts or contacting the employer direct; 5: The employer contacted the individual; 6: Continued working in a previous internship; 7: Prepared public examinations; 8: Started a business; 9: Other forms)
tourn_first	Type of journey in first job (Full-time, Part-time)
tjourn_act	Type of journey in current job (Full-time, Part-time)
isco_fj	Type of occupation in first job, following ISCO-08 classification (1 to 9 categories: Managers; Professional; Technicians and associate professionals; Clerical support workers; Service and sales workers; Skilled agricultural, forestry and fishery workers; Craft and related trades workers; Plant and machine operators, and assemblers; Elementary occupations)
isco_cj	Type of occupation in current job, following ISCO-08 classification (1 to 9 categories: Managers; Professional; Technicians and associate professionals; Clerical support workers; Service and sales workers; Skilled agricultural, forestry and fishery workers; Craft and related trades workers; Plant and machine operators, and assemblers; Elementary occupations)
time_job	Time spent from graduation until starting working (Continuity in previous job, Less than 3 months, From 3 to 6 months, From 6 to 12 months, From 1 year to 1.5 years, From 1.5 to 2 years, Over 2 years)
fj_ccaa	Autonomous Region or country of the first job
cj_ccaa	Autonomous Region or country of the current job
fj_sit_pro	Professional situation in the first job (Trainee, Permanent contract, Fixed contract, Independent worker)
sit_pro	Professional situation in the current job (Trainee, Permanent contract, Fixed contract, Independent worker)

Table 1. Variables definition (cont.)

E. Other social or economic variables	
Variable	*Definition*
unemp_res	Unemployment in the Autonomous Region or country of residence of the graduate. Due to the lack of information of the region of residence in the 2014 wave, it was built by combining information on the University region for those who did not move since getting the Degree and the information about the region they moved to for those who did.
ho_type	Type of household (Unipersonal, Household with children under 25 years old, Other type of household)
year	It indicates whether the individual is from the 2014 or the 2019 wave.

There are some aspects of the dataset that are worth mentioning. First, the objective indicators of overqualification (*obj_first_overq* and *obj_act_overq*) have been built following the Over-qualification rate (OQR) proposed by Eurostat (2016).[1] The definition would state that individuals are overqualified if they have tertiary education (between the categories 5 to 8 of the International Standard Classification of Education (ISCED)) and are working at an occupation between the categories 4 to 9 of the International Standard Classification of Occupations (ISCO-08). Second, almost all the interviewed individuals (more than 95% of the sample) have worked at least once in their lifetime, while around 79% are working at the time of the interview. The percentage is quite different for individuals interviewed in 2014 (73.1%) and in 2019 (84,8%). Third, due to the nature of our survey, we cannot study overqualification for postgraduates who work as graduates, since there is not sufficient information to do that distinction in both waves.[2] Fourth, we have excluded individuals with military occupations, independent workers, individuals who work helping in a family business and those whose current or first job is outside the European Union, except for the United Kingdom. We have also excluded observations that are missing for the main variables involved in the analysis. Table 2 offers a summary of descriptive statistics for the variables used in this work, considering whether they are available in the first job, in the current job or in both.

Table 2. Descriptive statistics summary

A. Job-education mismatches related variables						*Availability*
Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*	*First job/Current job*
sp_first_overq	47428	.308	.462	0	1	First
sp_act_overq	39466	.173	.378	0	1	Current
obj_first_overq	47428	.327	.469	0	1	First
obj_act_overq	39466	.217	.412	0	1	Current
first_hmismatch[(a)]	47428	1.085	0.745	0	2	First
act_hmismatch[(a)]	39466	0.991	0.708	0	2	Current
sp_out_overq	39466	.144	.351	0	1	Both
obj_out_overq	39466	.131	.338	0	1	Both
improve_hmismatch	39466	.151	.357	0	1	Both

[1] In the case of horizontal mismatch, it has not been possible to build an objective indicator in line with Eurostat (2016), since the criteria to match education field and occupation cannot be applied in our data.

[2] The Spanish Statistitical Office conducted in 2019 an additional survey, specific for Master graduates. It is part of our future research agenda to analyze job-education mismatches at the Master level. Unfortunately, this additional survey was not conducted in 2014.

Table 2. Descriptive statistics summary (cont.)

B. Individual characteristics						*Availability*
Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*	*First job/Current job*
male	47428	.400	.490	0	1	Both
age(a)	47428	1.634	0.776	1	3	Both
spanish	47428	.992	.091	0	1	Both
theor_sk(a)	38922	3.574	1.307	1	5	Both
pract_sk(a)	38880	3.821	1.291	1	5	Both
lang_sk(a)	38749	2.939	1.496	1	5	Current
it_sk(a)	38738	3.279	1.310	1	5	Current
soc_sk(a)	38858	4.135	1.104	1	5	Current
manag_sk(a)	38797	3.864	1.193	1	5	Current
ict(a)	47428	2.043	0.578	1	3	Current
lang2	47428	.940	.236	0	1	Current
C. Study related variables						*Availability*
Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*	*First job/Current job*
stud_abroad	47428	.155	.362	0	1	Both
grant_cv	47428	.071	.257	0	1	Both
priv_univ	47428	0.137	0.344	0	1	Both
field_stud(a)	47428	3.214	1.099	1	5	Both
pract_out	47428	.299	.458	0	1	Both
postgrad	47422	.423	.494	0	1	Both

D. Job and job search related variables						*Availability*
Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*	*First job/Current job*
jsearch_1	47428	.320	.467	0	1	First
jsearch_2	47428	.212	.408	0	1	First
jsearch_3	47428	.075	.263	0	1	First
jsearch_4	47428	.365	.481	0	1	First
jsearch_5	47428	.170	.375	0	1	First
jsearch_6	47428	.088	.283	0	1	First
jsearch_7	47428	.146	.353	0	1	First
jsearch_8	47428	.012	.107	0	1	First
jsearch_9	47428	.131	.338	0	1	First
tjourn_first	47428	.327	.469	0	1	First
isco_fj(a)	47428	3.178	1.679	1	9	First
time_job(a)	47428	2.146	2.009	0	6	First
fj_sit_pro(a)	47428	2.523	0.784	1	3	First
tjourn_act	39466	.182	.386	0	1	Current
isco_cj(a)	39466	2.734	1.351	1	9	Current
sit_pro(a)	39466	2.241	0.615	1	3	Current

E. Other social or economic variables						*Availability*
Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*	*First job/Current job*
unemp_res	38904	15.015	5.362	3.15	28.6	Current
ho_type(a)	31162	2.334	0.800	1	3	Current

(a)Categorical variable with more than two categories. Frequency table reported in Table A1 in the Appendix.

According to the figures in Table 2 and those in Table A1 in the Appendix, almost all the individuals are Spanish and 60% are women. Regarding age, 55.1% were younger than 30 years old at the time of the interview, 26.4% aged between 30 and 34 years old and 18.5% were older than 34 years old. Concerning the field of study, 9.5% studied Arts and Humanities and the same proportion studied Science, while Social and Legal Sciences was the chosen field by 45.4% of individuals, 21.6% studied Engineering and Architecture and 14.1% studied Health Sciences. Interestingly, there are gender differences in the choice of field of study. The presence of women is much higher than men in all fields expect in Engineering and Architecture: around 60% of women in Science studies, 65% in Arts and Humanities and in Social and Legal Sciences and 75% in Health Sciences, where only 31.6% studied Engineering and Architecture. Regarding the university, only 14% of individuals got the Degree in a private one, 15% studied abroad and 7% got an excellence grant.

Focusing on the variables related to job-education mismatches, around 31% of the individuals self-perceived to be overqualified in the first job, being the figure slightly higher (33%) when an objective indicator is considered. However, in the current job the figures are 17% (subjective indicator) and 21% (objective indicator). This lower incidence of overqualification in the current job points out to the capability of a proportion of individuals to leave this kind of mismatch. The factors that help individuals to improve their job match will be analysed in Section 5. Regarding horizontal mismatch in the first job (see Table A1 in the Appendix), around 24% of individuals perceive they are working in a field that matches what they have studied, 44% feel they have a weak mismatch (they work in a different but related field) and 32% suffer strong mismatch (they work in a completely different field). The figures in the current job are 25%, 50% and 25% respectively. Thus, it seems that leaving out horizontal mismatch is not an easy task. Tables 3 and 4 offer the incidence of overqualification and horizontal mismatch, respectively, for graduates of each wave.

Table 3. Incidence of overqualification

2014	*Self-perceived*	*Objective indicator*
First Job	36.67%	28.94%
Current job	25.62%	21.76%
Diff. current and first job	-11.05 pp	-7.18 pp
2019		
First Job	25.94%	35.77%
Current job	11.13%	21.61%
Diff. current and first job	-14.81 pp	-14.16 pp

Table 4. Incidence of horizontal mismatch (self-perceived)

2014	*No mismatch*	*Weak mismatch*	*Strong mismatch*
First Job	25.78%	44.83%	29.39%
Current job	28.01%	48.45%	23.54%
Diff. current and first job	+2.23 pp	+3.62 pp	-5.85 pp
2019			
First job	22.32%	42.86%	34.82%
Current Job	23.60%	50.90%	25.50%
Diff. current and first job	+1.28 pp	+8.04 pp	-9.32 pp

36.7% of the individuals who graduated in 2010 (data from 2014) considered themselves overqualified in their first job, while it was only the case for 25.9% of those who graduated in 2014 (data from 2019 wave). However, if we use an objective indicator to define overqualification, we obtain that 28.9% of graduates in 2010 are overqualified in their first job, while the number for graduates in 2014 is of 35.8%. Regarding overqualification in their current job, which would refer to their occupation four years after the graduation, we have that 25.6% of those who graduated in 2010 perceive themselves as overqualified in 2014, while only 11.1% of the graduated in 2014 feel the same in 2019. Alternatively, if we consider an objective indicator, the figures are similar in both waves, 21.8% and 21.6%, respectively. The information above shows there is an important difference between the proportion of overqualified individuals in our sample when we consider the objective indicator and when we use the self-perceived one. Regarding the objective indicator case, results for the first job might be surprising, since the proportion of overqualified graduates is higher for 2019 (35.77%) than for 2014 (28.94%). However, we should consider that the many labour market indicators, such as unemployment rate, were worse in 2014 (24.44%, INE) than in 2010 (19,86%, INE). Moreover, since the self-perceived indicator depends on the individual perception of his own state, two workers with the same qualifications and occupation might declare different mismatch status (De Oliveira, et al., 2000; Bajo, 2003). In addition to that, the expectations and mental health of individuals during the recession might have also affected to the graduates' answers, since recessions affect negatively to self-reported measures of life satisfaction (Morgan and O'Connor, 2021). Regardless of the indicator used, the incidence of overqualification is always lower four years after graduation. Furthermore, this reduction between the first and current job is always higher for the graduates in 2014 which might suggest that persistence in overqualification could be stronger for graduates in 2010. This may be related with the recession period suffered in Spain between 2008 and 2014, as stated by some authors (Cedefop, 2015)

Concerning the horizontal job-education mismatches, in Table 4 we observe that 74.2% of the graduated in 2010 perceive a strong or weak horizontal mismatch in their first job, while for graduates in 2014 the proportion is of 77.7%. The difference is even more noticeable if we review the figures for strong horizontal mismatches, which affect to 29.4% of the graduates in 2010 and 34.8% of the 2014 ones, again in their first job after graduation. Comparing those findings with the perceived horizontal mismatches in the current job, we find the percentage of individuals with horizontal mismatch decreases in both surveys. Nevertheless, the graduates in 2014 still perceive more horizontal mismatches (76.4%) than the graduates in 2010 (72,0%). We also see that the percentage of individuals who do not suffer horizontal mismatch or do it in a weak manner increases. This happens in both waves. However, the change in horizontal mismatches from the first occupation to the position four years after graduation is not the same for 2010 and graduates in 2014. Although the difference is not so evident as in the overqualification case, our preliminary results point to a higher probability of leaving strong horizontal mismatches for graduates in 2014, which reinforces the idea that the probability of suffering job-education mismatches is higher in recession periods.

The previous figures correspond to marginal distributions. In Tables 5 and 6 we look at conditional distributions, more specifically, at the incidence of mismatches in the current job conditional on the mismatch status at the first job, for overqualification and horizontal mismatch respectively. Considering self-perceived overqualification, we observe in Table 5 that around half of the individuals who were overqualified at the first job manage to leave out overqualification, but the figures are quite different in both waves: 38% in 2014 and 64% in 2019. If instead we use the objective indicator, the percentage of those overqualified in the first job who get a good match in the current job is lower, 43%, again with important differences across waves, 32% in 2014 and 50% in 2019. Despite the different magnitudes depending on the indicator used, the pattern of better options to leave out overqualification for those graduated in 2014 is observed.

Table 6 offers the conditional distribution for horizontal mismatch. We observe that among those suffering strong horizontal mismatch in the first job, 37% improved (weak mismatch or no mismatch). The figure for those graduated in 2010 is 33%, while for those graduated in 2014 is around 40%. Again, these figures show how leaving mismatch seemed to be easier in 2019 than in 2014.

Table 5. Conditional distribution of overqualification in the current job

Self-perceived indicator	**Current Job**	
Full sample	Not Overqualified (%)	Overqualified (%)
Fj: Not Overqualified	95.58	4.42
Fj: Overqualified	50.35	49.65
2014		
Fj: Not Overqualified	93.59	6.41
Fj: Overqualified	37.71	62.29
2019		
Fj: Not Overqualified	96.88	3.12
Fj: Overqualified	63.87	36.13

Objective indicator	**Current Job**	
Full sample	Not Overqualified (%)	Overqualified (%)
Fj: Not Overqualified	94.00	6.00
Fj: Overqualified	42.93	57.07
2014		
Fj: Not Overqualified	94.93	5.07
Fj: Overqualified	31.71	68.29
2019		
Fj: Not Overqualified	93.22	6.78
Fj: Overqualified	49.53	50.47

Notes: Fj stands for “first job”. In each row, the incidence of overqualification in the current job conditional to the overqualification status in the first job.

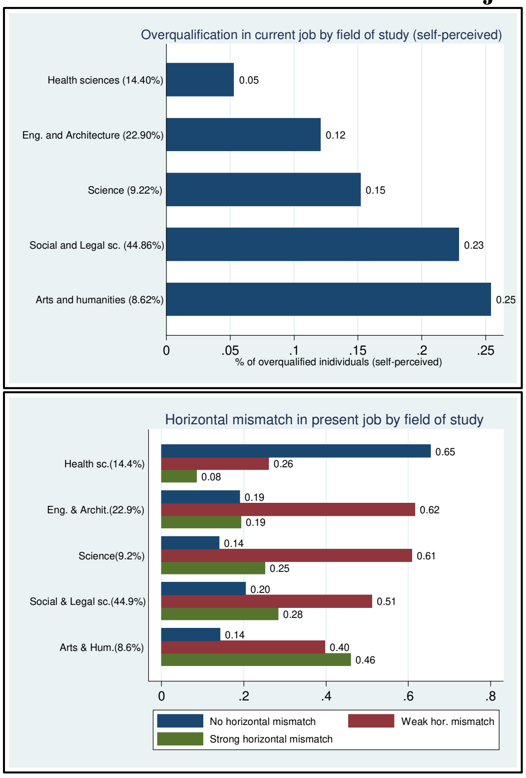
Table 6. Conditional distribution of horizontal mismatch in the current job

	Current Job		
Full sample	No Mismatch (%)	Weak Mismatch (%)	Strong Mismatch (%)
Fj: No Mismatch	78.32	15.51	6.17
Fj: Weak Mismatch	7.75	83.73	8.52
Fj: Strong Mismatch	10.34	27.14	62.52
2014			
Fj: No Mismatch	83.13	11.97	4.91
Fj: Weak Mismatch	8.60	83.27	8.13
Fj: Strong Mismatch	8.97	23.66	67.37
2019			
Fj: No Mismatch	74.15	18.58	7.27
Fj: Weak Mismatch	7.07	84.10	8.83
Fj: Strong Mismatch	11.19	29.28	59.53

Notes: Fj stands for "first job". In each row, the incidence of horizontal mismatch in the current job conditional to the horizontal mismatch status in the first job.

Another remarkable fact concerning job-education mismatches is the incidence across education fields. Figure 1 below shows, for each field of study, the incidence of overqualification (based on self-perception) and horizontal mismatch in the current job, in the bottom and top panels respectively. As it can be observed, the highest incidence of mismatches is among those graduated in Arts and Humanities or Social and Legal Sciences, where those graduated in Health Sciences suffer this phenomenon in a quite low proportion.

Figure 1. Job-education mismatches in the current job by education field



4. Econometric methodology

In the next section we will estimate several econometric models to explain the probability of job-education mismatches and the probability of leaving out a mismatch state. As we saw in Table 1, we measure overqualification through a binary indicator that takes the value 1 if the individual is overqualified. In the case of a horizontal mismatch the variable of interest is a categorical variable with three categories that represent the strength of the mismatch. This suggests the use of binary response models in the former case and ordered response models in the latter one. This type of models are very well known and have been used in the literature in many different contexts.

In our analysis, the dependent variables of interest (overqualification and horizontal mismatch) are only observed for those individuals who are working. If we are interested in the probability of being mismatched in the labour market given the individual's characteristics and other factors, there is a potential bias which comes from the selection of individuals into employment. The importance of this bias depends, among other factors, on the proportion of selected observations. In our specific case, if employed individuals represent a very high proportion of the sample, the selection bias will not be an issue to control for. However, if there is a non-negligible proportion of individuals who do not work, the sample selection must be accounted for.

In the case of nonlinear models, the traditional Heckman's approach, that was first formulated for the case of a linear model (Heckman, 1979), cannot be directly applied. Let us first consider sample selection in a binary probit model. Let y_1^* be the latent variable for the equation of interest and y_2^* the latent variable for the selection equation.[3] The model is formulated as follows:

$$y_1^* = x_1'\beta_1 + u_1$$
$$y_2^* = x_2'\beta_2 + u_2$$

where x_1' and x_2' are two sets of explanatory variables and β_1 and β_2 are parameter vectors to estimate. The observability rule for the binary indicators y_1 and y_2 is given by:

$$y_1 = 1(y_1^* > 0)$$
$$y_2 = 1(y_2^* > 0)$$

In our case, y_1 is the binary indicator for overqualification and y_2 the binary indicator for being employed. Note that y_1 is only observed if $y_2 = 1$ (sample selection). The error terms u_1 and u_2 of both equations are assumed to be independent of (x_1, x_2) and to follow this conditional bivariate normal distribution:

[3]To simplify notation, we omit the subindex for the individuals in all variables.

$$\begin{pmatrix} u_1 \\ u_2 \end{pmatrix} \Bigg| x_1, x_2 \Bigg) \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right)$$

where ρ is the correlation coefficient between the error terms of both equations. The conditional probability of interest is given by:

$$E[y_1 | y_2 = 1, x_1, x_2] = Pr[y_1 = 1 | y_2 = 1, x_1, x_2]$$

The expression for this probability, that uses properties of the truncated normal distribution, can be found in Wooldridge (2010) or Greene (2018), among others. The model is estimated by Maximum Likelihood and there are three types of observations that contribute to the likelihood function: $\{y_2 = 0, (y_1 = 0, y_2 = 1), (y_1 = 1, y_2 = 1)\}$. Once the model is estimated, we can test for the existence of sample selection bias by considering $H_0: \rho = 0$ and $H_1: \rho \neq 0$. If H_0 is not rejected, there is no evidence of sample selection bias and the estimation of the univariate probit model for y_1 with the available selected sample leads to consistent estimators. The sign of ρ informs about how unobservable factors affecting both observed outcomes are correlated.

As in all nonlinear models, the estimated coefficients do not inform about the magnitude of the effect of a change in one explanatory variable on the conditional probability of interest. The partial effects are computed as the partial derivatives of the conditional probability

$$\frac{\delta Pr[y_1 = 1 | y_2 = 1, x_1, x_2]}{\delta x_1}$$

assuming that x_1 is a continuous explanatory variable. For discrete regressors, differences instead of derivatives must be computed. For example, if x_1 is a gender indicator (and assuming for simplicity that there are no other covariates in the equation of interest), the average difference on this conditional probability for males and females is given by:

$$Pr[y_1 = 1 | y_2 = 1, x_1 = 1, x_2] - Pr[y_1 = 1 | y_2 = 1, x_1 = 0, x_2]$$

The partial effects are not constant. They are a nonlinear function of all the explanatory variables and all the parameters. Thus, a partial effect can be estimated for each observation. The estimated average partial effect is simply the sample average across observations of these estimated effects. Alternatively, we can compute partial effects at specific values of the explanatory variables. Given the nonlinearity of the partial effects, the standard errors can be computed through the Delta method once the variance-covariance matrix of the estimated coefficients is obtained.

If our variable of interest is ordered, as we mentioned that happens with the measure of horizontal mismatch, we should formulate an ordered choice model. Again, the horizontal mismatch variable is only observed for those who are working, which leads to sample selection. Accounting for sample selection in an ordered choice model can be done in a similar way we have seen for the probit case. The ordered choice model with sample selection can be formulated as follows in the latent variable framework:

$$y_1^* = x_1'\beta_1 + u_1$$
$$y_2^* = x_2'\beta_2 + u_2$$

where all elements have the same interpretation we saw in the previous model. The difference with the probit case appears in the observability rule for the ordered variable y_1. To keep it simple, let us consider that y_1 can take three values, $\{0,1,2\}$ as is the case in our context: $y_1 = 0$ represents no horizontal mismatch, $y_1 = 1$ is for weak mismatch and $y_2 = 1$ for strong mismatch. Then, we observe y_1 and y_2 according to the following rule:

$$y_1 = \begin{cases} 0 & if \quad y_1^* \leq \mu_1 \\ 1 & if \quad \mu_1 < y_1^* \leq \mu_2 \\ 2 & if \quad y_1^* > \mu_2 \end{cases}$$

$$y_2 = 1(y_2^* > 0)$$

where μ_1 and μ_2 are parameters to be jointly estimated with β_1 and β_2. For the error terms u_1 and u_2 we assume the same distribution as before, i.e., a bivariate normal distribution conditional on (x_1, x_2), with zero mean vector and correlation ρ between the two error terms. Again, there are different types of observations that contribute to the likelihood. In this case, we have:

$$\{y_2 = 0, (y_1 = 0, y_2 = 1), (y_1 = 1, y_2 = 1), (y_1 = 2, y_2 = 1)\}$$

The conditional probabilities of interest are given by:

$$Pr[y_1 = j | y_2 = 1, x_1, x_2] \text{ for } j = 0, 1, 2$$

As in the previous case, the partial effects of interest are the partial derivatives of these conditional probabilities with respect to continuous explanatory variables (differences for discrete regressors). We can compute partial effects on the conditional probability of each of the alternatives $j = 0, 1, 2$. For instance, if our interest is to see how a variable affects the probability of suffering strong mismatch, we should compute partial derivatives with respect to $Pr[y_1 = 2 | y_2 = 1, x_1, x_2]$.

The above-mentioned features of the partial effects, i.e. they are not constant, they depend nonlinearly on all the regressors and parameters is still true. Also, how to obtain estimated average partial effects and the corresponding standard errors follows the same logic explained for the probit case. More details about sample selection in ordered probit models can be found, for example, in Greene and Hensher (2010).

5. Estimation results

In this section we present the estimation results of econometric models for the probability of suffering job-education mismatches, either overqualification or horizontal mismatch, both at the first job after graduation and at the current job. We also investigate the factors that play a role in the probability of leaving mismatch. We estimate all models with the whole sample, including the 2014 and the 2019 waves. For each model considered, we have estimated several specifications including different groups of variables (see panels B, C and D in Table 2) to check the explanatory power of each group. Throughout this section, we report the results including all the variables, as well as region dummies (or country dummies for those working overseas) and a dummy for year.[4]

5.1. Overqualification in the first job

As we have already mentioned, the data allow us to consider two different measures of overqualification based, respectively, on a subjective indicator (self-perception) and on an objective indicator (according to the individual's occupation).

[4] Results with alternative specifications are available from the author upon request.

Table 7. Estimated average partial effects for overqualfication in the first job
Subjective indicator (Probit model)

2019	-0.144***	*Occupation (ISCO-08) (ref: managers)*	
	(0.003)	Professionals	-0.062***
Male	-0.001		(0.015)
	(0.004)	Technicians & assoc. prof.	0.188***
Spanish	-0.005		(0.015)
	(0.018)	Clerical support workers	0.298***
ICT knowledge (ref: basic)			(0.016)
Advanced	-0.007	Service and sales workers	0.551***
	(0.005)		(0.016)
Expert	-0.012*	Skilled agric/forest/fish workers	0.439***
	(0.006)		(0.044)
Speaks ≥2 languages	-0.022***	Craft and related trades workers	0.483***
	(0.007)		(0.027)
Study-related variables		Plant and machine operators	0.522***
Studied abroad	-0.021***		(0.028)
	(0.005)	Elementary occupations	0.566***
Excellence grant	-0.014**		(0.018)
	(0.007)	*Time to find first job (ref: stay in the job during studies)*	
Private university	-0.028***	Less than 3 months	-0.053***
	(0.005)		(0.005)
Field of study (Ref: Arts and Humanities)		From 3 to 6 months	-0.031***
Science	-0.006		(0.006)
	(0.007)	From 6 to 12 months	-0.038***
Soc. and Legal sc.	-0.000		(0.006)
	(0.006)	From 1 year to 1.5 years	-0.047***
Eng.and Architecture	-0.020***		(0.006)
	(0.007)	From 1.5 to 2 years	-0.033***
Health sciences	-0.082***		(0.008)
	(0.007)	More than 2 years	-0.026***
Internship outside degree	0.002		(0.006)
	(0.004)	*Type of contract (ref: internship trainee)*	
Job-related variables		Permanent contract	0.035***
Part-time job	0.093***		(0.005)
	(0.004)	Fixed-term contract	0.090***
			(0.005)
Observations		47428	
Adjusted Pseudo-R^2		0.370	
p-value joint sign. test		0.000	

Notes: In parentheses, robust standard errors for the average partial effects obtained from the Delta method. Probit estimated coefficients are available upon request; Region and types of job search dummies included in the model; *** p<0.01, ** p<0.05, * p<0.1

Regarding overqualification in the first job, we consider a probit model where the dependent variable is the binary indicator of being overqualified. We use the sample of those individuals that have ever had a job, that represent more than 95% of the sample. Given this high percentage, sample selection does not represent an issue here. The set of explanatory variables is composed of individual characteristics, study-related variables and first job characteristics. Additionally, we include region (CCAA) dummies as well as the year indicator. Results when the subjective indicator is used are reported in Table 7, which offers the average partial effects.[5]

Regarding personal characteristics we can state that, other things equal, gender is not significant, as stated in previous studies regarding the Spanish case (Flores, 2020; Montalvo, 2013 or Albert and Davia, 2018). Receiving an excellence or collaboration grant, speaking two or more languages, having studied abroad or studying in a private university significantly reduce the probability of being overqualified, which is in line with the results obtained by Albert and Davia (2018) or Flores (2020). Studies for other countries have similar results, such as Brunello and Cappellari (2008), who obtained that Italian graduates from public universities have higher risks of suffering overqualification than graduates from private institutions. Nevertheless, as stated by Albert and Davia (2018), this result is possibly dependent on the individual socio-demographic background and institutional factors.

As stated in part of the literature (Blázquez and Mora, 2010), obtaining high marks are associated with lowering the risk of overqualification. Therefore, considering that receiving an excellence or collaboration grant is related with having high marks, our results are consistent with the obtained in the previous literature. Moreover, this variable can be considered as a proxy for knowledge acquirement after graduation (Blázquez and Mora, 2010) or even with individual’s ability, which can let us control for part of the existing individual heterogeneity.[6]

On the contrary, the field of study is a very relevant determinant of overqualification, as stated by many authors in several studies (Erdisek, 2017; Blázquez and Mora, 2010; Albert and Davia, 2018; Dolton and Vignoles, 2010; Verhaest and Omey, 2010). Having a degree in Arts and Humanities, which is our reference category, increases the probability of being overqualified compared to Engineering or Health Sciences. No significant differences were found between Arts and Humanities and Social and Legal Sciences graduates. Graduates in the field of Health Sciences are those who have the lowest risk of being overqualified in their first job, with 8.16 pp less, on average, than those who hold a university degree in Arts and Humanities, once we control for other factors. These results are consistent with the existing literature. For instance, Ortiz and Kucel (2008), Carroll and Tani (2013) or Edisek (2017) state that degrees in Health Sciences are aimed at very specific occupations with discipline-specific skills needed, while Art and Humanities or Social Sciences have a wider scope, therefore having higher chances of leading to overqualification or, more generally, mismatches.

Concerning job related characteristics, we find that the way that individuals search for a job affects the probability of being overqualified. In line with Blázquez and Mora(2010), Caroll and Tani (2015) or McGuinness et al. (2016) using Internet or the newspaper as a search tool increases the probability of being overqualified, which is also the case when graduates decide to use a temporary work agency,

[5] Probit estimated coefficients are available upon request;
[6] Unfortunately, we do not have panel data to better control for individual unobserved heterogeneity.

which usually tends to focus more on finding a job quickly rather than finding an adequate one, especially taking into account the low quality of temporary jobs in Spain (Albert and Davia, 2018; McGuinness et al. 2016). This also seems to happen when individuals use personal contacts, increasing their probability of overqualification by 1.44 pp. On the contrary, using more formal ways of job search, as public or university services, reduces the probability of being overqualified. Other options for the first job search such as being contacted directly by the employer, preparing public examinations or continuing working in a previous internship decrease the risk of overqualification. Continuing working in a previous internship has the highest impact on the overqualification probability, reducing it by 6.82pp.

Compared to graduates who continued after graduation in the job they had during their studies, individuals who looked for a different job, regardless of the time spent from graduation until they found it, seem to reduce their risk of overqualification, other things equal. This would possibly be explained by the fact that the qualification required for the graduate's job during the degree is lower than the graduate's university education.

Other job-related variables such as the work schedule, the professional situation or the region or country of the first job have a significant effect. For instance, working part-time (with respect of full-time) increases the probability of being overqualified by 9.33 pp. Trainees have lower probability of being overqualified than those with a permanent or fixed-term contract. This result, that is in line with Erdisek (2016), may seem reasonable since internships usually are more related with individuals' education.

Regarding the region or country of the first job (we do not report the average partial effects in Table 7 for a sake of simplicity) we find that compared to Madrid, the category of reference, graduates working in the Basque Country, La Rioja or Catalonia suffer less overqualification risk, while for those who work in the United Kingdom or in a country of the EU (outside Spain, France, Germany or the UK), the probability of overqualification in the first job increases. The latter can be explained by the fact that many Spanish graduates may seek an international experience after graduation, to increase their language skills, which is specially the case for the United Kingdom and learning English. Therefore, having the first job after graduation in the UK has the highest impact on the probability of overqualification, increasing it by 12 pp with respect to graduates who had their first job in Madrid.

Regarding occupation, we see that, as it could be expected, individuals working in the generally less qualification needed occupations have the highest probabilities of being overqualified, comparing to the reference category, managers.

Finally, the *year* variable let us know, other things equal, differences in the overqualification risk between individuals who graduated in 2010 and those who did so in 2014. This variable has a very significant effect, showing that individuals who graduated in 2014 have a lower perception of being overqualified, 14 pp less than those who graduated in 2010. This result must be interpreted with caution, since we do not have information about when graduates got their first job after graduation.[7] In terms of unemployment, in 2014 the Spanish economic situation was even worse than in 2010[8], although it was starting to recover.

Table 8 reports the estimated model when the objective indicator of overqualification is used. We offer the average partial effects.[9]

Table 8. Estimated average partial effects for overqualification in the first job
Objective indicator (Probit model)

2019	0.092***		
	(0.004)		
Male	-0.008*		
	(0.004)		
Spanish	-0.044**		
	(0.022)		
ICT knowledge (ref: basic)			
Advanced	0.018***		
	(0.006)		
Expert	-0.055***		
	(0.008)		
Speaks ≥2 languages	-0.043***		
	(0.009)		
Study-related variables			
Studied abroad	-0.025***		
	(0.006)		
Excellence grant	-0.050***		
	(0.008)	*Time to find first job (ref: stay in the job during studies)*	
Private university	-0.106***	Less than 3 months	-0.037***
	(0.006)		(0.006)
Field of study (Ref: Arts and Humanities)		From 3 to 6 months	-0.031***
Science	-0.114***		(0.007)
	(0.009)	From 6 to 12 months	-0.013*
Soc. and Legal sc.	0.035***		(0.007)
	(0.008)	From 1 year to 1.5 years	-0.043***
Eng.and Architecture	-0.148***		(0.008)
	(0.009)	From 1.5 to 2 years	-0.018*
Health sciences	-0.221***		(0.009)
	(0.008)	More than 2 years	-0.017**
Internship outside degree	0.007		(0.007)
	(0.004)	*Type of contract (ref: internship trainee)*	
Job-related variables		Permanent contract	0.076***
Part-time job	0.072***		(0.006)
	(0.005)	Fixed-term contract	0.132***
			(0.005)
Observations		47428	
Adjusted Pseudo-R^2		0129	
p-value joint sign. test		0.000	

Notes: In parentheses, robust standard errors for the average partial effects obtained from the Delta method. Probit estimated coefficients are available upon request; Region and types of job search dummies included in the model; *** p<0.01, ** p<0.05, * p<0.1

[7] The information is coded into intervals and does not allow to know in detailed when the individual started to work (see Table 1) since, as mentioned in the data description, the information about the time of graduation is not completely precise. Moreover, for those who have spent more than two years to find a job since graduation, there is no way to know, even approximately, when they got their first job.

[8] Unemployment rate for Spain (OECD). In 2010: 19.88%. In 2014: 24.45%.

[9] Estimated coefficients are available upon request.

From them we can state that the results regarding personal and study characteristics are consistent with the existing literature and the obtained for the self-perceived overqualification estimation. However, in this case, we find that the gender indicator is significant at a 10% level, but its partial effect magnitude is very low.

Regarding the field of study, the most relevant difference between the results obtained between the objective and self-perceived indicator is that in the latter case we found no significant difference between Arts and Humanities graduates and Social and Legal sciences or Sciences, while now we obtain that at a 99% confidence level the graduates in Social and Legal science have higher chances of being overqualified (3.5pp more than Arts and Humanities graduates) and Sciences graduate a lower one (11.4pp less than Arts and Humanities graduates). For the rest of the fields of study, we find similar results, where Health sciences graduates are the ones with the lowest risk of overqualification.

Concerning job related variables, we find very similar results to the obtained in the self-perceived case, at least in sign and significance. Therefore, results concerning the job search type, the work schedule or the contractual situation remain alike, with no relevant differences worth mentioning. However, the Autonomous Region or countries of the first job seem to have different effects. For instance, in this case we obtain that individuals whose first job is settled in any autonomous region, except for Ceuta or Melilla, have higher probabilities of being overqualified than if they work in Madrid. The same happens for individuals who have their first job after graduation in the UK. The latter suffer an increase of 22.3 percentage points in their overqualification risk in their first job, under the constructed objective indicator.

Regarding the variable *year* we obtain that, the probability of overqualification is clearly higher for individuals who graduated in 2014 (9.2 pp more than those graduated in 2010). These results are contrary to the obtained for the self-perceived indicator. Although we might think this makes no sense, we should take into account that a 61.2% of the sample found their first job during the first year after graduation. This can explain the obtained results, since the economic situation in 2014-2015 was worse than in 2010-2011, at least regarding unemployment rates, which is a good proxy to understand how the labour market evolves. Moreover, the objective indicator does not depend on the perceived situation of each individual, which might be affected by the economic expectations (Morgan, and O'Connor, 2021), which were clearly worse in 2010 than in 2014. Nevertheless, this difference in the *year* variable found with both indicators possibly needs a deeper analysis in line with what Verhaest and Omey (2010) state on their survey regarding the possible different outcomes we can get employing different measures regarding overeducation.

5.2. Overqualification in the current job

The variables regarding overqualification in the current job are only observed for those individuals who are currently working. Our interest is to measure the probability of being offered a job for which the individual is qualified, given her characteristics. At the time of the interview there is a non-negligible proportion of individuals who are not employed (around 21%), so the potential bias stemmed from the self-selection into employment should be taken into account. Thus, we estimate probit models with sample selection. The dependent variable in the equation of interest is the binary indicator for being overqualified in the current job. We analyse the role of individual characteristics, study-related and current job-related variables. We also include a set of skills regarding different aspects such as the use of ICT, management ability, etc. in the current job[10]. Besides the dummy variable for year, we include as well an indicator of whether the individual was overqualified in the first job that we interact with the time indicator in order to analyse the persistence of overqualification. In the selection equation into employment we consider individual characteristics and study-related variables, as well as two variables not included in the overqualification probit equation: the unemployment rate in the Autonomous Region or overseas country the individual lives in and the type of household, mainly whether the individual lives alone.[11] This type of instruments have been used in the literature that analyses labour outcomes accounting for endogeneity issues (Angrist and Evans, 1998; Carrasco, 2001; Arkes, 2010)

Results for the self-perceived overqualification indicator are reported in Table 9. Focusing on personal characteristics results from that table, we can deduce that, other things equal, gender is again statistically insignificant. The results indicate that individuals over 34 years old have a higher risk of suffering overqualification in their current job than individuals under 30 years old. This could be explained since possibly over 34 years old individuals were already working when they started the degree studies and would possibly have more financial responsibilities and recurring costs that complicates the possibility of leaving a job to search for a better matched one.

[10] This information is referred to the time of the interview and the current job, which prevents us to include them as explanatory variables in the first job equations.
[11] The information on the CCAA is only available for working individuals. To generate the CCAA for those not working (to assign the corresponding unemployment rate) we have followed the process described in Table 1, block E, for the *unemp_res* variable

Table 9. Estimated average partial effects for overqualification in the current job
Self-perceived indicator (Probit model with sample selection)

	Overqualification (Self-perceived)
2019	-0.099***
	(0.007)
Overq. in first job (both years)	0.196***
	(0.007)
In 2014	0.338***
	(0.015)
In 2019	0.144***
	(0.006)
Male	-0.001
	(0.002)
Age intervals (re: <30 years old)	
30-34 years old	0.002
	(0.003)
>34 years old	0.028***
	(0.004)
Spanish	0.032**
	(0.013)
Theoretical skills (ref: None)	
Moderate	-0.068***
	(0.006)
Expert	-0.106***
	(0.007)
Practical skills (ref:None)	
Moderate	-0.017***
	(0.006)
Expert	-0.036***
	(0.006)
Languages skills (ref:None)	
Moderate	-0.0180***
	(0.004)
Expert	-0.044***
	(0.005)
IT skills (ref:None)	
Moderate	-0.017***
	(0.005)
Expert	-0.015***
	(0.006)
Soc skills (ref:None)	
Moderate	0.016**
	(0.008)
Expert	0.011
	(0.008)
Management skills (ref:None)	
Moderate	-0.014*
	(0.008)
Expert	-0.045***
	(0.008)
Studied abroad	-0.007*
	(0.004)

Table 9. (Cont.)

Coll. or excellence grant	-0.005
	(0.006)
Private university	-0.005
	(0.004)
Field of study (ref: Arts and Humanities	
Science	-0.012*
	(0.007)
Soc. and Legal sciences	-0.010*
	(0.006)
Engineering.and Architecture	-0.024***
	(0.008)
Health sciences	-0.038***
	(0.008)
Internship outside degree	-0.003
	(0.003)
Postgraduate studies	-0.011***
	(0.003)
Part-time job	0.036***
	(0.004)
Current job occupation (ISCO-08) (ref: managers)	
Professionals	-0.021**
	(0.008)
Technicians & assoc. prof.	0.071***
	(0.009)
Clerical support workers	0.136***
	(0.010)
Service and sales workers	0.269***
	(0.014)
Skilled agric/forest/fish workers	0.092**
	(0.041)
Craft and related trades workers	0.153***
	(0.022)
Plant and machine operators	0.191***
	(0.027)
Elementary occupations	0.237***
	-0.021**
Type of contract (ref: trainee)	
Permanent contract	0.015***
	(0.006)
Fixed-term contract	0.024***
	(0.005)
Observations	38872
Selected sample observations	30720
p-value joint sign. test	0.000
Estimated value of ρ	0.018
p-value (H_0: ρ=0)	0.908

Notes: Robust standard errors for the average partial effects obtained from the Delta method. Probit estimated coefficients are available upon request; Regarding skill variables we have only reported the coefficients for two (Moderate and Expert) of the described categories in Table 1, results for the rest are available upon request; Region dummies included in the model; *** p<0.01, ** p<0.05, * p<0.1.

Regarding skills relevant for the current job, the results show that, other things equal, the higher theoretical, practical, IT or languages skills the individuals declared to have, the lower is the probability of being overqualified. Graduates who declare to have good or expert management skills suffer less risk of overqualification (-3.56pp and -4.53pp respectively) than those who declare having no management skills. We find no clear results for social skills, which is not a surprising result since soft skills are more transversal and may not be really related to the job-education match.

Concerning study related variables, almost no significant effects were found for graduating from a private university, for having studied abroad or for receiving an excellence or collaboration grant during the degree, which differs from the first job overqualification results.

Other variables related with studies show statistically significant results to explain the probability of being overqualified. For instance, individuals who have undertaken graduate studies see their risk of overqualification reduced in 1.09 percentage points, which is consistent with Albert and Davia (2018) results for Spanish university graduates in 2010. Regarding the field of study, we obtain similar results as in the first job models, since graduates of the Arts and Humanities field, which is our category of reference, are those with the highest risk of overqualification and individuals with a degree in Health Sciences have the lowest probability (3.78pp less than Arts and Humanities graduates). However, the difference between graduates in the Science field and the Arts and Humanities one is only significant at a 10% level, while in this case we obtain that graduates in Social and Legal Sciences have a 0.99pp lower probability of overqualification in the current job than individuals with a degree in Arts and Humanities.

Regarding job characteristics we can state that the work schedule, the contractual situation or the place of work have a significant effect on the probability of being overqualified. For instance, once we control for other factors, working part-time instead of full-time increases that probability by 3.60pp, while having a fixed-term or permanent contract raises it by 1.53 and 2.35 percentage points respectively, with respect of graduates who currently work under a trainee contract. The results for the regional dummies (not reported in the table for simplicity) reflect that that compared to Madrid, working in Aragón, Castilla-La Mancha or Catalonia reduces the probability of overqualification, while working in Ceuta, Germany or the UK increases it. These results are consistent with the previously suggested scenario where many recent graduates may want to seek learning languages in other countries, having to accept to work in jobs they are overqualified for.

Occupation control variable (*isco_cj*) report similar reports as the obtained for the first job overqualification analysis, using the corresponding occupations variable (*isco_fj*), since individuals in elementary and other low required qualification occupations present higher probabilities of overqualification than those who work as managers.

For the current job analysis, we again obtain that the variable *year* has a negative and significant effect, implying that individuals who graduated around 2014 have a lower risk of being overqualified (-9.91pp) than those who did it around 2010. Although it is not a perfect measure of the effects of the recession period on overqualification, this variable let us have some important information about it. The different time periods from graduation until the interview in both waves are a key point to understand the outcome of the *year* variable, since 2010-2014, corresponding to individuals from the 2014 wave, was a clear recession period in Spain, while the corresponding one to the graduates in 2014 (2014-2018) was a recovery one. Therefore, the *year* variable in the current job analysis can be clearly associated with the effect of the recession period on the probability of being overqualified, which is positive, as stated by other authors (Cedefop, 2015; Wolbers, 2003).

As explained above, including the first job overqualification variable gives us information about the persistence of overqualification in the Spanish labour market for university graduates. In this case, we obtain that individuals who were overqualified in the first job have a 19.6pp higher probability of being overqualified in their job four years after graduation, compared to those who did not suffer overqualification in their first job. If we take a closer look at our results, we can observe that persistence seems to be different between waves. For instance, individuals who graduated in 2010 and were overqualified in the first job see their current job overqualification probability increase in 33.84pp, while those who graduated in 2014 only suffer an increase of 14.38pp. The latter results would imply that not only being overqualified would be more probable for graduates in 2010, which was derived from the *year* variable results, but also individuals have more chances to remain overqualified. Determinants of leaving out overqualification will be explored in more detail in subsection 5.5. Regarding sample selection bias we do not find evidence of it in the reported estimated model that includes all groups of variables in the equation of interest.[12]

The estimation results with the objective indicator of overqualification are shown in Table 10, using the same specification we have used with the subjective indicator.

[12] In a base model that only includes the indicator for overqualification in the first job, the dummy year variable and their interaction, there is strong evidence of selection bias, but the evidence becomes weaker as we include additional groups of explanatory variables. For the model that includes all variables we have also estimated an standard probit model and, as expected, the results are very similar to those reported in Table 9. All these estimation results are available upon request.

Table 10. Estimated average partial effects for overqualification in the current job
Objective indicator (Probit model with sample selection)

	Overqualification (Objective)
2019	-0.010**
	(0.005)
Overqualification first job (both years)	0.322***
	(0.008)
In 2014	0.405***
	(0.017)
In 2019	0.292***
	(0.006)
Male	-0.001
	(0.003)
Age intervals (re: <30 years old)	
30-34 years old	0.010**
	(0.004)
>34 years old	0.006
	(0.005)
Spanish	0.002
	(0.017)
Theoretical skills (ref: None)	
Moderate	-0.109***
	(0.009)
Expert	-0.168***
	(0.009)
Practical skills (ref:None)	
Moderate	-0.032***
	(0.008)
Expert	-0.079***
	(0.008)
Languages skills (ref:None)	
Moderate	0.002
	(0.005)
Expert	-0.017***
	(0.005)
IT skills (ref:None)	
Moderate	-0.003
	(0.006)
Expert	0.013*
	(0.007)
Soc skills (ref:None)	
Moderate	0.050***
	(0.009)
Expert	0.053***
	(0.008)
Management skills (ref:None)	
Moderate	-0.029***
	(0.010)
Expert	-0.056***
	(0.010)
Studied abroad	-0.011**
	(0.005)

Table 10. (Cont.)

Coll. or excellence grant	-0.017**
	(0.007)
Private university	-0.017***
	(0.005)
Field of study (ref: Arts and Humanities	
Science	-0.041***
	(0.008)
Soc. and Legal sciences	0.015**
	(0.006)
Engineering.and Architecture	-0.045***
	(0.007)
Health sciences	-0.072***
	(0.008)
Internship outside degree	0.003
	(0.004)
Postgraduate studies	-0.023***
	(0.004)
Part-time job	0.014***
	(0.005)
Type of contract (ref: trainee)	
Permanent contract	0.062***
	(0.007)
Fixed-term contract	0.019***
	(0.007)
Observations	38872
Selected sample observations	30720
p-value joint sign. test	0.000
Estimated value of ρ	0.710
p-value (H_0: ρ=0)	0.000

Notes: Robust standard errors for the average partial effects obtained from the Delta method. Probit estimated coefficients are available upon request; Regarding skill variables we have only reported the coefficients for two (Moderate and Expert) of the described categories in Table 1, results for the rest are available upon request; Occupation not included due to the definition of the objective indicator; Region dummies included in the model; *** p<0.01, ** p<0.05, * p<0.1.

From it we deduce similar results as the obtained for the self-perceived indicator. However, we now find that age has mixed effects, since we get that individuals aged between 30 and 34 years old have 0.99 percentage points more than graduates under 30 years old, but we do not find a relevant difference between individuals aged over 34 years old and those under 30. Other personal or study related determinants such as attending a private university, having studied abroad or receiving an excellence or collaboration grant are non-significant in the self-perceived case but they cause a significant reduction in the probability of overqualification for the objective indicator.

The skills variables results are the expected for most of the cases, since the better theoretical knowledge, practical or management skills individuals declare to have, the lower is their probability of overqualification. A lower risk of being overqualified is also observed for individuals who declare to have good or excellent language skills. However, while for the self-perceived case we found clear evidence in the case of IT skills, we now need a 90% confidence level to state that the results are significant. Social skills seem to increase the probability of mismatch, which, in line with what has been commented for the self-perceived indicator, can be hard to interpret.

The field of study is again a relevant determinant of overqualification in the current job. Results are on the same line as the obtained for the self-perceived indicator, since we get that individuals with a degree in Health Sciences have the lowest chances of being overqualified (7.23 less percentage points than individuals from the reference category, the Arts and Humanities field). However, in this case, we obtain that graduates from Social and Legal Sciences suffer, on average, an increase of 1.46 percentage points in their probability of overqualification compared to Arts and Humanities graduates. This is consistent with the results obtained by Albert and Davia (2018) for Spanish university graduates but differs with our previous self-perceived indicator results.

Regarding most of the job variables we observe resembling outcomes to the obtained in the self-perceived scenario. For instance, we obtain that working part-time increases the probability of it by 1.36 percentage points, while having a trainee contract reduces it (compared to individuals with a fixed-term or permanent contract). Concerning the region or country of the current job, we get similar results to the obtained for the first job analysis under the objective indicator, but contrary to the results of the current job overqualification probability using the self-perceived indicator. For instance, we get that working in Madrid reduces the risk of overqualification compared to almost every other autonomous region, while working in the United Kingdom four years after graduation reduces the probability of overqualification in 2.33pp compared to working in Madrid. The latter is also contrary to the results for the analysis of overqualification in the first job. Nevertheless, the result for the UK is only significant at a 90% confidence level.

The *year* variable it is only significant at a 90% confidence level, but the sign is negative, contrary to what we had in the analysis of overqualification in the first job using the objective indicator, but consistent with what we obtain in the self-perceive analysis for the current job. However, the magnitude of the effect is very small, since individuals who graduated in 2014 would only benefit from a 1.03pp reduction on their probability of overqualification, compared with graduates in 2010. As discussed previously, the variable *year* can be a good proxy to measure the effect of the recession period on the probability of overqualification. Nevertheless, the results obtained with the self-perceived indicator show a much more relevant effect of the recession period than the one obtained with the objective indicator.

Finally, the first job overqualification variable included in this model indicates that, under the objective measure, overqualification seems to be a persistent problem. Other things equal, individuals who were overqualified in the first job suffer an increase of 32.2pp in the probability of being overqualified in their job four years after graduation. If we compare the results by year, we obtain that those overqualified in the first job who graduated in 2010 would suffer a 40.5pp increase in their probability of overqualification in their current job, while those graduated in 2014 would have a 29.2pp increase. This would imply that persistence is more pronounced in the recession period, which comprises graduates in 2010. The probability of leaving the overqualification state and its determinants will be analysed in section 5.5.

Regarding sample selection, the results are different from those obtained with the subjective indicator. The sign of the estimated ρ coefficient remains positive but there is now evidence of selection bias, even in the reported model that includes all groups of variables.

5.3. Horizontal mismatch in the first job

Horizontal mismatch happens when the individual's job does not match with her field of study. As mentioned earlier, the data offer three categories of mismatch: (i) no mismatch, if the individual is working in a job for which her field of study is appropriate; (i) weak mismatch, when the field of study does not perfectly match but is related to the knowledge required for her job; (iii) strong mismatch, if the individual's job is not related with her field of study.

Contrary to overqualification, for horizontal mismatch we only consider the self-perceived indicator. Eurostat (2016) also defines an objective indicator based on Wolbers (2003) and defined in terms of whether the field of study matches occupation (ISCO-08). However, the level of aggregation in Wolbers (2003) does not allow to use this strategy with our database.

The ordered nature of our dependent variable leads us to use an ordered choice model in which we consider the same set of explanatory variables used to analyse overqualification. For the first job, given that we use the available information for all individuals who have ever had a job and this represents more than 95% of the sample, we think it is reasonable to think that sample selection is not an issue.

The estimation results of an ordered probit model is shown in Table 11. We report the average partial effects on the probability of suffering strong horizontal mismatch at the first job.[13]

[13] The average partial effects of the explanatory variables on the probability of the other two alternatives (no mismatch, weak mismatch) are available from the authors upon request.

Table 11. Estimated average partial effects for strong horizontal mismatch in the first job (Probit model)

2019	0.010***	*Occupation (ISCO-08) (ref: managers)*	
	(0.003)	Professionals	-0.140***
Male	0.004		(0.013)
	(0.003)	Technicians & assoc. prof.	0.004
Spanish	-0.006		(0.013)
	(0.017)	Clerical support workers	0.127***
ICT knowledge (ref: basic)			(0.014)
Advanced	0.013***	Service and sales workers	0.379***
	(0.005)		(0.014)
Expert	0.005	Skilled agric/forest/fish workers	0.165***
	(0.006)		(0.045)
Speaks ≥2 languages	-0.007	Craft and related trades workers	0.253***
	(0.006)		(0.030)
Study-related variables		Plant and machine operators	0.327***
Studied abroad	-0.004		(0.032)
	(0.004)	Elementary occupations	0.370***
Excellence grant	-0.006		(0.018)
	(0.006)	*Time to find first job (ref: stay in the job during studies)*	
Private university	-0.018***	Less than 3 months	-0.097***
	(0.004)		(0.004)
Field of study (Ref: Arts and Humanities)		From 3 to 6 months	-0.031***
Science	-0.053***		(0.005)
	(0.008)	From 6 to 12 months	-0.079***
Soc. and Legal sc.	-0.125***		(0.005)
	(0.006)	From 1 year to 1.5 years	-0.066***
Eng.and Architecture	-0.115***		(0.006)
	(0.007)	From 1.5 to 2 years	-0.038***
Health sciences	-0.311***		(0.007)
	(0.007)	More than 2 years	-0.026***
Internship outside degree	0.007**		(0.006)
	(0.003)	*Type of contract (ref: internship trainee)*	
Job-related variables		Permanent contract	0.086***
Part-time job	0.050***		(0.004)
	(0.004)	Fixed-term contract	0.073***
			(0.004)
Observations		47428	
Adjusted Pseudo-R^2		0.203	
p-value joint sign. test		0.000	

Notes: In parentheses, robust standard errors for the average partial effects obtained from the Delta method. Probit estimated coefficients are available upon request; Region and types of job search dummies included in the model; *** p<0.01, ** p<0.05, * p<0.1

From the estimation results we find that gender has no significant effect in the probability of suffering a horizontal mismatch in the first job, which is consistent with the results provided by Rodríguez-Esteban, Vidal, Vieira (2019) for the 2010 Spanish university graduate's case. However, other works from the existing literature state that gender has a significant impact on the probability of suffering a horizontal mismatch. For instance, Hensen et al. (2009) in her survey for job-education mismatches in the Netherlands, states that males usually have more jobs within their field of study, avoiding horizontal mismatches. On the contrary, Wolbers (2003) obtains that male school leavers have a field of education mismatch more frequently than females. Anyway, our results are not comparable to the latter. No significant results were found for some other personal characteristics, such as the nationality, speaking two or more languages, having studied abroad or receiving an excellence or collaboration grant. Most of these variables were significant on the first specification, however, once we include job and job search variables, they no longer provide significant information. Regarding ICT knowledge we find that individuals with advanced knowledge have 1.32pp more probability of suffering a strong mismatch than individuals with basic knowledge. The results concerning ICT knowledge are quite surprising and opposite to the ones obtained by Rodríguez-Esteban et.al (2019), where they analysed horizontal mismatches for the graduates in 2010 in Spain. Our potential explanation is that ICT knowledge is quite transversal and can be useful to a wide range of jobs in different areas, which maybe make easier for those with high expertise in ICT to be working in areas that do not match their studies. This is also supported by Rodríguez-Esteban et.al (2019) who states that acquiring general competences and not specific ones may increase the horizontal mismatch probability, since following Nordin et al. (2010) or Sicherman and Galor (1990) it facilitates mobility between sectors. On the same line, finding that doing an internship outside the degree programme increases the probability of suffering strong mismatch is possible. Moreover, similar results are found in Rodríguez-Esteban et. al. (2019).

On the other hand, the field of study has a relevant impact in the probability of suffering a horizontal mismatch. For instance, being graduate in Health Sciences reduces the probability of having a strong mismatch by 31.1pp with respect with those who have an Arts or Humanities degree. As expected, the probability of suffering a strong horizontal mismatch is always significantly higher for individuals with an Arts and Humanities degree. These results are consistent with the existing literature, as they reflect what Wolbers (2003), Rodríguez-Esteban et. al. (2019) or Robst (2007) obtain. The latter studies field of study mismatches regarding college graduates residing in the United States.

Regarding the job search type, we obtain that using Internet or newspapers advertisements or a temporary work agency to find a job increase the risk of suffering a strong mismatch by 1.05 pp and 5.21 pp respectively. On the contrary, continuing in a previous internship, being contacted by the employer, using public or university employment services or preparing public examinations reduce the probability of being strongly horizontally mismatched in the first job.

Other job characteristics such as the work schedule, the type of contract or the time spent to find a job since graduation also have an impact on suffering this type of mismatch. For instance, individuals who work part-time have a higher probability to be strongly mismatched than those with a full-time work schedule, increased by 5pp. This is in line with the results obtained by Boudarbat and Chernoff (2012) for recent Canadian graduates.

Graduates who worked as interns during their first job have less chances of being strongly mismatched than individuals with a permanent or fixed-term contract. Regarding the time spent from graduation until starting a job, we find that graduates who continue working where they were doing so during their degree have a higher probability of being strongly mismatched than individuals who spend some time looking for a job. Individuals who find a job in less than 3 months since graduation (but do not continue in a previous one) are the ones with the lowest chances of suffering a strong horizontal mismatch.

As expected, graduates working in elementary occupations, plant and machine operators or other usually low qualification required occupations, tend to have higher probabilities of being strongly horizontally mismatched compared with individuals who work as managers.

About regional effects (not reported in the table for simplicity), individuals whose first job after graduation is in Andalucía, the Balearic Islands, Canary Islands, Casilla-La Mancha, Catalonia, Comunitat Valenciana, Galicia, Murcia, Navarra, La Rioja, Ceuta or the Basque Country present a significant lower risk of strong horizontal mismatch than graduates whose first job was in Madrid. On the contrary, individuals whose first job is in the UK or Germany have more chances of being strongly horizontally mismatched. The latter could have a similar explanation as in the overqualification case, since many Spanish graduates may seek an international experience after graduation, to increase their language skills, which is specially the case for the United Kingdom. Therefore, willing to accept not only lower qualification jobs, which would explain higher overqualification incidence, but also working in other fields unrelated with their university studies.

Regarding the variable *year*, we obtain that individuals from the 2014 wave have a significantly higher probability of being strongly mismatched in their first job than graduates in 2010. The difference is of 1.01pp, not very relevant but significant at a 1% level.

5.4. Horizontal mismatch in the current job

As we did in Section 5.2, we consider horizontal mismatches in the current job controlling for the potential sample selection of individuals into employment. Thus, we estimate an ordered probit model with sample selection. We consider the same specification used for overqualification in the current job. Again, the instrumental variables that we use for the selection equation are some household characteristics and the unemployment rate in the region or country of residence at the time of the interview. Estimation results from the equation of interest shown in Table 12.

Table 12. Estimated average partial effects for strong horizontal mismatch in the current job (Probit model with sample selection)

	Hor. Mismatch (Self-perceived)
2019	-0.012**
	(0.005)
Weak mismatch first job (both years)	0.169***
	(0.004)
In 2014	0.169***
	(0.006)
In 2019	0.169***
	(0.004)
Strong mismatch first job (both years)	0.387***
	(0.008)
In 2014	0.445***
	(0.016)
In 2019	0.366***
	(0.008)
Male	0.008**
	(0.003)
Age intervals (re: <30 years old)	
30-34 years old	0.003
	(0.004)
>34 years old	0.054***
	(0.004)
Spanish	0.018
	(0.016)
Theoretical skills (ref: None)	
Moderate	-0.146***
	(0.010)
Expert	-0.202***
	(0.001)
Practical skills (ref:None)	
Moderate	-0.074***
	(0.001)
Expert	-0.113***
	(0.001)
Languages skills (ref:None)	
Moderate	0.008*
	(0.005)
Expert	0.004
	(0.005)
IT skills (ref:None)	
Moderate	0.006
	(0.006)
Expert	0.034***
	(0.007)
Soc skills (ref:None)	
Moderate	0.047***
	(0.009)
Expert	0.044***
	(0.001)
Management skills (ref:None)	
Moderate	-0.009
	(0.001)
Expert	-0.023**
	(0.001)
Studied abroad	-0.002
	(0.004)

Table 12. (Cont.)

Coll. or excellence grant	0.002
	(0.006)
Private university	0.007
	(0.004)
Field of study (ref: Arts and Humanities	
Science	-0.027***
	(0.008)
Soc. and Legal sciences	-0.076***
	(0.007)
Engineering.and Architecture	-0.069***
	(0.008)
Health sciences	-0.130***
	(0.009)
Internship outside degree	0.007**
	(0.003)
Postgraduate studies	0.004
	(0.003)
Part-time job	0.0150***
	(0.005)
First job occupation (ISCO-08) (ref: managers)	
Professionals	-0.099***
	(0.010)
Technicians & assoc. prof.	-0.024**
	(0.01)
Clerical support workers	0.039***
	(0.011)
Service and sales workers	0.188***
	(0.014)
Skilled agric/forest/fish workers	-0.038
	(0.042)
Craft and related trades workers	0.072**
	(0.029)
Plant and machine operators	0.175***
	(0.035)
Elementary occupations	0.198***
	(0.023)
Type of contract (ref: trainee)	
Permanent contract	0.011**
	(0.006)
Fixed-term contract	-0.000
	(0.006)
Observations	38872
Selected sample observations	30720
p-value joint sign. test	0.000
Estimated value of ρ	0.125
p-value (H_0: ρ=0)	0.058

Notes: Robust standard errors for the average partial effects obtained from the Delta method. Probit estimated coefficients are available upon request; Regarding skill variables we have only reported the coefficients for two (Moderate and Expert) of the described categories in Table 1, results for the rest are available upon request; Region dummies included in the model; *** p<0.01, ** p<0.05, * p<0.1.

We focus on the results reported in the last column, that includes all the groups of variables considered. Looking at the personal determinants we can see that, once we control for other factors, gender is now statistically significant, although its magnitude is small (the risk of suffering a strong horizontal mismatch is 0.8pp higher for men than for women). We also find that age is significant, since individuals over 34 years old present a 5.42 percentage points higher probability of being strongly horizontally mismatched in the current job compared to graduates under 30 years old. However, we do not find evidence of a difference between individuals under 30 years old and those who have between 30 and 34 years old.

Regarding skill variables, we find that management and languages skills report almost no significant effects, while having better practical and theoretical skills clearly reduce the probability of suffering a strong horizontal mismatch. Concerning IT skills we only found that individuals who declare to have good or expert IT skills present a higher probability of being strongly mismatched (1.62 and 3.41 percentage points respectively), this might be unexpected but is in line with what we obtained in the analysis of the first job horizontal mismatch determinants. In the case of management skills we have similar results as for IT skills, however in this case individuals who declare to have good skills see their probability reduced in a higher amount than those with expert skills. Having better social skills seem to significantly increase the probability of having a strong horizontal mismatch in the current job. Other individual or studies related factors such as having a postgraduate degree, having studied abroad or receiving a collaboration or excellence grant during their degree have no statistically significant effect on the probability of suffering this type of mismatch. The latter, in addition to the skill variables results, reinforces the previously stated idea that acquiring general competences and not specific ones may increase the horizontal mismatch probability, as individuals have more opportunities to move between sectors. Other authors such Caroleo and Pastore (2018) find that the influence of this type of factors on all job mismatches is not always true.

Concerning the field of study, we obtain the expected results since individuals with an Art and Humanities degree are those with the highest probability of being strongly horizontally mismatched in their current job, while those with a degree in Health Sciences present the lowest risk (13 percentage points less than graduates with a degree from the Art and Humanities field). These results reinforce the obtained for the first job analysis regarding horizontal mismatches and are again in line with Wolbers(2003), Rodríguez-Esteban et. al. (2019) or Robst(2007).

Regarding job related characteristics we obtain similar results to the observed in the analysis of the first job horizontal mismatches for the variables included in both models. Despite this, there are some differences. For instance, the effect of the professional (contractual) situation of the individual is now statistically insignificant. Concerning the location of the current job, we find again that working in Madrid seems to increase the probability of strong mismatch, comparing to most of the other Spanish regions. However, we find that even if in the first job individuals who work in Madrid have a lower probability of being horizontally mismatched than those who work in the United Kingdom or Germany, this is no longer valid for the current job analysis, where the difference is insignificant. This is consistent with what we previously suggested regarding the seek for international experiences and learning languages that individuals may have just after graduation, but possibly four years later they look for a better job-education match.

The variable *year* states that the probability of suffering a strong horizontal mismatch is 1.16pp lower for individuals who graduated in 2014 compared to those who did so in 2010. This would imply that the recession period could have had a negative impact in the Spanish labour market, increasing the probability of suffering a strong horizontal mismatch.

Finally, we obtain that the horizontal mismatch status in the first job has a significant effect on the probability of suffering a horizontal mismatch in the job four years after graduation. For instance, other things equal, if the individual suffers a weak mismatch in their first job, the probability of strong mismatch in the current one increases by 16.9pp compared to individuals who had no horizontal mismatch, while if the graduate suffers a strong mismatch in the first job, this probability increases by 38.7pp. Therefore, it seems that horizontal mismatches might present a persistent character. However, persistence is also related with the economic performance. We find that the probability of suffering a strong mismatch if the individual has a strong horizontal mismatch in the first job increases by 44.5pp for graduates in 2010 and 36.6pp for the 2014 ones (compared to individuals who present no horizontal mismatch in the first job).

The estimated ρ coefficient is statistically significant only at 10% level, showing not very strong evidence of sample selection bias.[14]

5.5. Determinants of getting out of job-education mismatches

As we have seen, both overqualification and horizontal mismatches can be a persistent phenomenon that depends on the economic performance but also on individual and job characteristics. Then, what are the factors behind the success in leaving overqualification or improving the horizontal mismatch state? To analyse the probability of getting out of a job-education mismatch, we consider those individuals who were in that situation in the first job and analyse their current job mismatch state. In the case of horizontal mismatch, we consider individuals who suffered strong or weak horizontal mismatches. Then we estimate models that take as dependent variable the binary indicator of leaving or improving the mismatch state in the current job. To clarify this, we will estimate two probit models for the probability of leaving overqualification, one with the objective indicator and another one with the self-perceived measure, and a probit model for the probability of improving the horizontal mismatch state.

Focusing on those who experienced a mismatch at the first job implies a potential sample selection bias. We have controlled for it by estimating probit models with sample selection, jointly estimating the

[14] Given this result, we have also estimated an standard probit model, finding very similar results regarding the variables of interest, as expected. Estimation results are available upon request.

probability of being mismatched at the first job. Our results do not reveal evidence of selection bias.[15] Thus, we offer estimation results based on standard probit models.

As potential determinants of leaving the mismatch we have considered individual and study-related characteristics as well as variables referred to the first job. Since we try to explain the evolution from the first to the current job, we do not include variables specific to the current job.

Table 13 offers the estimated average partial effects for the probability of leaving overqualification (in the first and second columns under the subjective and objective indicators, respectively) or improving the horizontal mismatch (in the third column). The latter is defined as moving from strong mismatch to a weak or no mismatch, as well as moving from a weak mismatch to a good match.

[15] Estimation results when controlling for the potential sample selection are available from the authors upon request.

Table 13. Estimated average partial effects for the probability of leaving or improving a job-education mismatch state

	Overqualification (Self-perceived)	Overqualification (Objective indicator)	Horizontal mismatch
2019	0.241***	0.130***	0.024***
	(0.009)	(0.009)	(0.005)
Male	-0.015	-0.013	-0.010**
	(0.010)	(0.009)	(0.005)
Age intervals (ref: <30 years old)			
30-34 years old	-0.013	-0.012	0.006
	(0.010)	(0.010)	(0.005)
>34 years old	-0.126***	-0.075***	-0.038***
	(0.015)	(0.014)	(0.007)
Spanish	-0.116***	-0.030	-0.046*
	(0.044)	(0.039)	(0.024)
ICT knowledge (ref:basic)			
Advanced	0.043***	0.008	0.003
	(0.013)	(0.013)	(0.007)
Expert	0.090***	0.086***	0.005
	(0.017)	(0.017)	(0.009)
Speaks ≥2 languages	0.042**	0.039**	0.025***
	(0.017)	(0.018)	(0.009)
Studied abroad	0.079***	0.052***	0.026***
	(0.013)	(0.012)	(0.006)
Excellence grant	0.076***	0.050***	0.004
	(0.019)	(0.019)	(0.009)
Private university	0.019	0.034**	0.006
	(0.015)	(0.015)	(0.007)
Field of study (ref: Arts and Humanities)			
Science	0.112***	0.164***	0.027***
	(0.020)	(0.020)	(0.009)
Soc. and Legal sciences	0.105***	0.040***	0.049***
	(0.015)	(0.014)	(0.007)
Engineering.and Architecture	0.188***	0.192***	0.061***
	(0.018)	(0.018)	(0.008)
Health sciences	0.290***	0.312***	0.162***
	(0.022)	(0.021)	(0.011)
Internship outside degree	0.038***	0.033***	0.008*
	(0.010)	(0.009)	(0.005)
Postgraduate studies	0.102***	0.107***	0.032***
	(0.010)	(0.009)	(0.005)

Table 13. (Cont.)

	Overqualification (Self-perceived)	Overqualification (Objective indicator)	Horizontal mismatch
Part-time job	0.049***	0.075***	0.085***
	(0.009)	(0.009)	(0.005)
First job occupation (ISCO-08) (ref: managers)			
Professionals	0.133**		0.048***
	(0.065)		(0.013)
Technicians & assoc. prof.	0.123*		0.130***
	(0.065)		(0.014)
Clerical support workers	0.081		0.141***
	(0.065)		(0.014)
Service and sales workers	0.111*		0.267***
	(0.065)		(0.014)
Skilled agric/forest/fish workers	0.057		0.149***
	(0.091)		(0.048)
Craft and related trades workers	0.103		0.268***
	(0.073)		(0.031)
Plant and machine operators	0.076		0.215***
	(0.074)		(0.032)
Elementary occupations	0.078		0.232***
	(0.066)		(0.018)
Time to find first job (ref: stay in the job during studies)			
Less than 3 months	0.002	-0.006	-0.005
	(0.013)	(0.013)	(0.007)
From 3 to 6 months	-0.029**	-0.022	0.004
	(0.015)	(0.015)	(0.008)
From 6 to 12 months	-0.056***	-0.055***	-0.011
	(0.015)	(0.015)	(0.008)
From 1 year to 1.5 years	-0.052***	-0.047***	-0.033***
	(0.017)	(0.017)	(0.008)
From 1.5 to 2 years	-0.079***	-0.062***	-0.028***
	(0.020)	(0.020)	(0.010)
More than 2 years	-0.131***	-0.110***	-0.052***
	(0.016)	(0.015)	(0.008)
Type of contract (ref: trainee)			
Permanent contract	-0.173***	-0.179***	-0.048***
	(0.017)	(0.015)	(0.007)
Fixed-term contract	0.004	0.024*	0.073***
	(0.015)	(0.013)	(0.007)
Observations	10912	11734	29006
Pseudo-R^2	0.147	0.125	0.138
p-value joint sign. test	0.000	0.000	0.000

Notes: Robust standard errors for the average partial effects obtained from the Delta method. Probit estimated coefficients are available upon request; Occupation not included in the second column due to the definition of the objective indicator; Region dummies included in the model; *** p<0.01, ** p<0.05, * p<0.1.

From this table we observe that some personal characteristics such as having advanced or expert ICT knowledge or speaking more than two languages have a positive impact on the probability of getting out of overqualification. Concerning age, we obtain that individuals over 34 years old present a 12.6pp lower probability of getting out of overqualification than graduates under 30 years old.

Most of the variables related with studies also have a positive impact on that probability. It is the case for having studied abroad, receiving an excellence or collaboration grant during the degree, having done practices outside the degree programme or holding a postgraduate diploma. Regarding the field of study, we obtain that Arts and Humanities graduates are those with the lowest probability of getting out of overqualification, while individuals with a Health Sciences degree have the highest one.

Regarding job-related variables we get that many of them, such as the time spent since graduation until finding a job are significant. This can be capturing partly the individual's ability, and the results show that the longer it has taken to get a first job, the lower is the probability of leaving a mismatch. We also obtain that individuals who worked part-time in the first job have a higher probability of leaving the overqualification state in their current job (4.9pp more). This is an expected result, since those working part-time possibly have higher incentives to job mobility, and thus, to look for a job that better matches their qualification. Graduates who had a fixed-term contract in their first job have 17.3pp less probability than graduates who worked as a trainee in their first job. On the contrary, the occupation in the first job (ISCO-08) presents almost no statistically significant results for most of the categories. Nevertheless, having the first job in the UK has a very significant effect, increasing the probability of getting out of overqualification in the current job by 18.4pp. This is possibly related to the high incidence of overqualification among graduates who had their first job in the UK, as suggested in previous sections.

Finally, we should point out that the variable *year* shows that graduates in 2014 have 24.1pp more probability than graduates in 2010 of passing from being overqualified in their first job after graduation to no longer be in their current job (four years after graduation). This reinforces the idea previously stated, during the analysis of overqualification determinants, that recessions may not only increase the probability of overqualification but also its persistence.

Using the objective indicator (second column) we get very similar results for most of the variables considered. Remarkably, the variable *year* shows that the objective indicator also permits us to state that graduates in 2014 had more chances than those in 2010 to leave the overqualification state, but the estimated average effect is 13pp lower than under the self-perception indicator.

The third column of Table 13 displays the results of the model concerning the probability of improving the graduates' horizontal mismatch state from the first to the current job. There are some differences with the previous results for overqualification. Gender is now statistically significant at a 5% level, indicating that, other things equal, men have 10pp less probability than women to improve their horizontal mismatch status. Relevant differences are found between individuals under 30 years old and those over 34 years old. The latter would have 3.8pp less chances of improving their horizontal mismatch state with respect to their first job. On the contrary, other personal or study characteristics such as speaking two or more languages or receiving an excellence or collaboration grant have no effect on the probability of improving the graduates' horizontal mismatch state. The field of study results state that Health Science graduates have the highest probability, compared to those from the Arts and Humanities field, of improving their horizontal mismatch status.

Regarding job related variables we get that having a part-time schedule in the first job increases the probability of improving the horizontal mismatch state. This is also observed for individuals with a fixed-term contract in the first job, who show an increase of 7.3pp with respect with graduates who worked as trainee in the first job. Compared to the latter, graduates with a permanent contract have a reduction of 4.8pp in their probability of improving their mismatch status, which is expected, since this type of contracts may encourage individuals to stay at their job post.

Concerning the *year* variable, we obtain that graduates in 2014 have a 2.4pp higher probability of improving their horizontal mismatch than individuals who finished their degree in 2010. As stated for the overqualification case, this suggests that recession periods significantly increase the persistence of job-education mismatches. However, the estimated magnitude of the effect shows that the impact of recessions on horizontal mismatches' persistence seems less severe than for the case of overqualification.

The estimation results shown in this section contribute to the literature by analysing job-mismatches from a broad perspective (both overqualification and horizontal mismatch), using different indicators of vertical mismatch (both subjective and objective indicators), analysing the impact of the economic crisis on job-education mismatches as well as the persistence of this phenomenon. However, they have some limitations. First, our data is a pool of two cross sections, which prevents us to control in a proper manner for unobserved individual heterogeneity. Nevertheless, we have used some variables that can partially capture individual's ability. Second, the available data does not contain precise information on some relevant aspects such as job mobility or previous labour experience. These factors might be relevant to explain job-education mismatches.

6. Conclusions and further research

In this paper we have analysed job-education mismatches amongst university graduates in the Spanish labour market. The aim of our analysis has been to understand what determines these mismatches, how persistent they are and how the 2008 Great Recession could have affected them. For this analysis we have used the Labour Insertion Survey for Recent University Graduates (EILU) in Spain, performed by the National Statistics Institute (INE) for years 2014 and 2019.

Two types of mismatches have been taken into consideration: overqualification and horizontal mismatch. We have also used two types of indicators for overqualification (self-perceived and objective). All of these job-education mismatches have been analysed for individuals' first job after graduation and at their job at the time of the interview.

From the methodological point of view, we have estimated probit models for overqualification and ordered probit models for horizontal mismatch at the first job. For the current job, we have considered the self-selection into employment, so we have estimated probit and ordered probit models with sample selection for overqualification and horizontal mismatch, respectively.

Concerning the probability of being overqualified at the start of graduates' careers we have found that job and study related characteristics play an important role, no matter what measure is used, subjective or objective. Receiving an excellence or collaboration grant during the degree studies, going to a private university or having studied abroad reduce the probability of overqualification, while working part-time increases it. Regarding the current job, we find some differences depending on the overqualification indicator used. As expected, many study-related variable lose explanatory power, except the education filed, which appears to be an important determinant to explain overqualification, both in the first and in the current job. This is also true for the horizontal mismatches. Interestingly, we find that skills play a different role to explain the probability of being overqualified or suffering horizontal mismatch. Concerning the persistence of mismatch, our results show, in line with previous literature, that regardless of the type of mismatch or measure we use, being mismatched at the first job after graduation significantly increases the probability of continuing being so four years later.

The economic performance can affect the chances of individuals of getting a job and also a job that matches their education. We find that graduates in 2014 have lower probabilities of being mismatched than those who graduated in 2010, which is not so clear when the objective indicator of overqualification is used. Moreover, regarding the probability of leaving overqualification or improving the horizontal mismatch state, our results clearly exhibit the effect of the recession; no matter the indicator used, graduates in 2014 have higher chances of getting out of a job-education mismatch.

As part of our research agenda, we plan to investigate more deeply what is behind the differences found when subjective and objective indicators are used to measure overqualification. This is especially interesting regarding the effect that recessions may have on self-perceived indicators, as has been stated in the previous literature in different contexts. Replicating this study at the Master level, using the data available for the 2019 wave of the EILU survey is also part of our future research agenda.

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Appendix

Table A1. Frequency table of categorical variables with more than two categories

Horizontal mismatch in first job	*Freq.*	*Percent*	*Cum.*
No horizontal mismatch	11331	23.89%	23.89%
Weak horizontal mismatch	20753	43.76%	67.65%
Strong horizontal mismatch	15344	32.35%	100.00%
TOTAL	47428		

Horizontal mismatch in present job	*Freq.*	*Percent*	*Cum.*
No horizontal mismatch	10064	25.50%	25.50%
Weak horizontal mismatch	19671	49.84%	75.34%
Strong horizontal mismatch	9731	24.66%	100.00%
TOTAL	39466		

Age group	*Freq.*	*Percent*	*Cum.*
<30 years old	26124	55.08%	55.08%
30-34 years old	12518	26.39%	81.48%
>34 years old	8786	18.52%	100.00%
TOTAL	47428		

Theoretical skills	*Freq.*	*Percent*	*Cum.*
None	4124	10.60%	10.60%
Low	4404	11.31%	21.91%
Moderate	7117	18.29%	40.20%
Good	11547	29.67%	69.86%
Excellent	11730	30.14%	100.00%
TOTAL	38922		

Practical skills	*Freq.*	*Percent*	*Cum.*
None	3535	9.09%	9.09%
Low	3283	8.44%	17.54%
Moderate	5414	13.92%	31.46%
Good	11007	28.31%	59.77%
Excellent	15641	40.23%	100.00%
TOTAL	38880		

Table A1. Frequency table of categorical variables with more than two categories (cont.)

Languages	*Freq.*	*Percent*	*Cum.*
None	9932	25.17%	25.17%
Low	7190	18.22%	43.38%
Moderate	6994	17.72%	61.11%
Good	6599	16.72%	77.83%
Excellent	8751	22.17%	100.00%
TOTAL	39466		

IT skills	*Freq.*	*Percent*	*Cum.*
None	5398	13.68%	13.68%
Low	5712	14.47%	28.15%
Moderate	9048	22.93%	51.08%
Good	11266	28.55%	79.62%
Excellent	8042	20.38%	100.00%
TOTAL	39466		

Social skills	*Freq.*	*Percent*	*Cum.*
None	2118	5.37%	5.37%
Low	1690	4.28%	9.65%
Moderate	4176	10.58%	20.23%
Good	12384	31.38%	51.61%
Excellent	19098	48.39%	100.00%
TOTAL	39466		

Management skills	*Freq.*	*Percent*	*Cum.*
None	2812	7.13%	7.13%
Low	2820	7.15%	14.27%
Moderate	6035	15.29%	29.56%
Good	13188	33.42%	62.98%
Excellent	14611	37.02%	100.00%
TOTAL	39466		

Information and communications technology	*Freq.*	*Percent*	*Cum.*
ICT knowledge: Basic	5520	14.01%	14.01%
ICT knowledge: Advanced	25958	65.87%	79.88%
ICT knowledge: Expert	7931	20.12%	100.00%
TOTAL	39409		

Table A1. Frequency table of categorical variables with more than two categories (cont.)

Field of study	*Freq.*	*Percent*	*Cum.*
Arts and humanities	4503	9.49%	9.49%
Science	4471	9.43%	18.92%
Social and Legal sciences	21537	45.41%	64.33%
Engineering and Architecture	10230	21.57%	85.90%
Health sciences	6687	14.10%	100.00%
TOTAL	47428		

Occupation in the first job ISCO 08	*Freq.*	*Percent*	*Cum.*
Managers	709	1.49%	1.49%
Professional	23729	50.03%	51.53%
Technicians and associate professionals	7500	15.81%	67.34%
Clerical support workers	5717	12.05%	79.39%
Service and sales workers	7359	15.52%	94.91%
Skilled agricultural, forestry and fish	118	0.25%	95.16%
Craft and related trades workers	345	0.73%	95.89%
Plant and machine operators, and assemb	306	0.65%	96.53%
Elementary occupations	1645	3.47%	100.00%
TOTAL	47428		

Time spent since graduation until start working	*Freq.*	*Percent*	*Cum.*
Continued at least 6 months in previous	12907	27.21%	27.21%
Time to find first job: <3 months	10851	22.88%	50.09%
Time to find first job: 3-6 months	5293	11.16%	61.25%
Time to find first job: 6-12 months	6018	12.69%	73.94%
Time to find first job: 1-1.5 years	4590	9.68%	83.62%
Time to find first job: 1.5-2 years	2687	5.67%	89.28%
Time to find first job: >2 years	5082	10.72%	100.00%
TOTAL	47428		

Professional situation in first job	*Freq.*	*Percent*	*Cum.*
Trainee	10110	21.32%	21.32%
Permanent contract	15230	32.11%	53.43%
Fixed-term contract	22088	46.57%	100.00%
TOTAL	47428		

Table A1. Frequency table of categorical variables with more than two categories (cont.)

Occupation in the current job ISCO 08	*Freq.*	*Percent*	*Cum.*
Managers	3870	9.81%	9.81%
Professional	22202	56.26%	66.06%
Technicians and associate professionals	13394	33.94%	100.00%
Clerical support workers	4503	11.41%	89.74%
Service and sales workers	3013	7.63%	97.37%
Skilled agricultural, forestry and fish	53	0.13%	97.50%
Craft and related trades workers	205	0.52%	98.02%
Plant and machine operators, and assemb	213	0.54%	98.56%
Elementary occupations	567	1.44%	100.00%
TOTAL	39466		

Professional situation in current job	*Freq.*	*Percent*	*Cum.*
Trainee	3870	9.81%	9.81%
Permanent contract	22202	56.26%	66.06%
Fixed-term contract	13394	33.94%	100.00%
TOTAL	39466		

House type	*Freq.*	*Percent*	*Cum.*
Unipersonal	6526	20.94%	20.94%
With children <25 y.o.	7694	24.69%	45.63%
Other type of households	16942	54.37%	100.00%
TOTAL	31162		