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The Reform of Curricula in the Spanish University System: How Well Matched Are New Bachelor's Degrees to Jobs

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Abstract: This study looks at how well bachelor's degree holders in Spain match into jobs five years after graduation. Based on workers' self-assessment, education–job mismatch is defined as the discrepancy between the formal qualifications that individuals earned at Spanish universities and those that are required by jobs. By estimating a multinomial logit model, this research identifies fields of study that are associated with increased likelihood of a particular educational mismatch status. Results indicate that university graduates from highly specialized bachelor's degree programs are more likely to work in a graduate job that is related to their field of education. In particular, graduates with degrees that entail specific human capital, such as health sciences degrees and hard science and engineering degrees, are more likely to be well-matched in their current jobs. In contrast, the results show a higher likelihood of over-qualification (recent graduates who are in non-graduate jobs) for social and legal sciences degrees and arts and humanities degrees. Gender appears to play no role in the matching process; however, the subject-specific knowledge that graduates have gained from their time in higher education is important. As a novelty, this study also identifies, for a sub-sample of workers, the process through which a good match is achieved—that is, how individuals self-select to accept jobs in which they can achieve a good match. The regression results are based on micro data from a nationally representative random sample of the first cohort of undergraduates after the Bologna curriculum reform.

Keywords: educational mismatch; EILU2019 survey; higher education; multinomial logit model; Spanish undergraduates

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1. Introduction

Economics emphasizes the central role of resource allocation in achieving efficiency. Economists distinguish between internal and external efficiency. The former is concerned with how well an economy uses its limited resources in production, while the latter relates to whether the results of economic activity are what society desires. If we narrow the analysis to higher education systems, external efficiency is frequently evaluated by connecting the higher education system's outputs to outcomes, including labor market outcomes [1]. Since degrees awarded are one of the principal outputs of higher education institutions (HEIs), studying the connection between university-issued credentials, such as degrees, and jobs in the graduate labor market is crucial when assessing the external efficiency of systems of higher education. The efficient allocation of supply and demand for skilled labor requires a match between the formal qualifications provided by HEIs and those required by jobs. Through the development of employability skills, higher education systems may also play an important role in improving the education–job match. In order to improve the employability of university graduates, the Spanish university system reformed its study plans in 2010, offering new bachelor's degrees and restructuring the contents of the old curricula (known as the Bologna reform). However, until relatively recently, labor market information on cohorts who graduated with new bachelor's programs has not been available to researchers, which has prevented study of the education–job matching in the Spanish graduate labor market after the reform of curricula. This article takes advantage of the opportunity provided to researchers by the *Encuesta de Inserción Laboral de titulados Universitarios* (EILU2019), which was carried out by the National Institute of Statistics of Spain (INE). The EILU2019 survey is a nationally representative random sample of the public and private universities that make up the Spanish university system, as well as the degrees granted by the Spanish HEIs. The data set contains interviews with the first graduates of the Spanish university curriculum reform. In particular, a total of 31,651 bachelor's degree holders from the 2013/2014 academic year were surveyed in 2019 (i.e., five years after graduation).

This article aims to investigate, using this graduate survey, how well the new undergraduate degrees in Spain fit into jobs. This topic is relevant not only to assessing the external efficiency of the Spanish higher education system (new curricula should demonstrate an awareness of the needs of the labor market), but also from an individual point of view because well-matched university graduates are expected to maximize their lifetime earning potential. The value associated with formal qualifications, expressed in terms of their ability to increase a graduate's earning potential, represents a significant area of interest. However, the study of skill mismatches is beyond the scope of this article and the EILU2019 survey, unlike surveys such as REFLEX, does not contain detailed information on skills acquired and required by jobs. In fact, a growing literature has focused on the phenomenon of occupational mismatch in many European countries; most studies have focused on educational mismatch, with a smaller literature on skill mismatch due to data limitations [2]. Furthermore, in the Spanish labor market in general, job titles are defined in terms of educational requirements that coincide with the levels and types of formal education. The UK is probably at the forefront of non-subject–specific recruitment (at least 50 percent of graduate recruitment is not subject-specific), but this trend is growing in Scandinavia and the United States [3]. Nevertheless, the main problem that arises from the current research is defining what is meant by "a good" education–employment match. The EILU2019 survey contains information on the undergraduates' self-assessment about the quality of the job match in their current positions at the time of the interviews in 2019, five years after graduation. The interviewees reported whether or not they worked in typical university degree-level jobs and whether or not their field of study was related to the job. Combining workers' responses to this self-assessment, this article identifies four educational match/mismatch statuses and the probability of falling into those statuses, following the methodology developed by Salas-Velasco [4]: adequate match, horizontal mismatch (or field-of-study mismatch), vertical mismatch (or over-education), and vertical and horizontal mismatch (or full mismatch). As a novelty, this paper also identifies, for a sub-sample of workers, the process through which a good match is achieved (i.e., how individuals self-select to accept positions in which they can achieve a good match).

The remainder of this paper is organized as follows: Section 2 reviews the literature and shows how it adds value to the current study; Section 3 describes the research method, including the incidence of educational mismatch in the Spanish graduate labor market, as well as the results of the econometric estimation of multinomial logistic regression; Section 4 focuses on the analysis of the matching process for a sample of workers; Section 5 discusses the main results; and Section 6 presents the main conclusions.

2. Background

The mismatch between the formal qualifications that people possess and those that are required by jobs is known as the education–job mismatch. The majority of theoretical and empirical studies on the topic of educational mismatch have mostly concentrated on vertical mismatch (also known as over-education and over-qualification), which occurs when an employee holds a position that requires less formal education than the employee already possesses. The discrepancy between the quantity of people's formal education and the level necessary for their jobs has been extensively researched in the labor and education economics literature since the release of Freeman's book *The Overeducated American* [5] (e.g., [6–9]). Horizontal mismatch (also known as field-of-study mismatch), which happens when professionals trained in one field work in another at their formal qualification level, has only lately been taken into account by the educational mismatch literature (for a review of the literature, see Somers et al. [10]).

2.1. Educational Mismatch among University Graduates: Theoretical Explanations

The majority of empirical studies on the mismatch between education and employment among university graduates have primarily focused on graduate over-education (e.g., [11]). Graduates who work in non-graduate positions are said to be over-educated, over-qualified, or vertically mismatched. The causes of graduate over-education have been the subject of some dispute in the literature. An imbalance between the supply and demand for labor input is a commonly cited cause. At the national level, there may be an oversupply of qualified employees compared to the structure of positions that are available in the economy, which could lead to over-qualification. Among the elements that have contributed to the deterioration of graduates' career prospects is the expansion of higher education [12]. Over the last three decades, many OECD countries have experienced rapid growth in educational enrollments at specific levels or in general. There was widespread credential or degree inflation. Younger people are more likely to work part-time or find casual jobs due to the growing number of higher education graduates entering the labor market each year, while many college graduates are employed in positions where a degree is not necessary and where the skills they learned in college are not fully utilized [13]. The expression "occupational filtering down" refers to this phenomenon. As higher education grows, more educated people are moving into lower-paying employment [14].

For example, young graduates in European nations such as Spain or Greece experienced substantial unemployment rates as a result of increased enrollment in higher education and the economic downturn. According to Eurostat (https://ec.europa.eu/eurostat, accessed on 14 December 2022), the unemployment rates in the second quarter of 2014 for tertiary education graduates (ISCED-97 levels 5 and 6) aged 25 to 29 were 37%, 24%, and 10% in Greece, Spain, and the EU-28, respectively. In the case of Poland, the growth in participation in higher education led to the youth making rapid transitions to employment with a poor education–job match, even though they showed high stability in their first employment [15]. Poland witnessed over-qualification as a result of the crowding out of university graduates [16]. However, the educational mismatch can also be traced to the job market's demand side. At the expense of middle-skill positions, employment growth is "polarizing" into relatively high-skill, high-wage jobs and low-skill, low-wage jobs [17]. The automation of routine work and integration of labor markets internationally are major contributors to the polarization of jobs [17]. Only if an economy is able to produce highly qualified employment in sectors such as biomedicine, telecommunications, etc., can it be expected that university graduates will hold complex jobs that are associated with a higher level of skill demand. Otherwise, college graduates will replace high school graduates in the workforce.

However, there is no widely accepted, comprehensive explanation of the education–job mismatch in the graduate labor market. The over-education phenomenon has been conceptualized and explained by some economists using the traditional (neoclassical) view of the labor market. In this respect, information issues may be the cause of labor market mismatches (imperfect information in the labor market). The "theory of screening" is at the heart of this viewpoint (e.g., [18]). The way by which the productive abilities of individuals are verified is known as screening because a worker's productivity in a given job is not known ex ante. Education is one tool used to sort people based on their skills and recognize those abilities with educational credentials [19]. University degrees are the most difficult to acquire due to the varied obstacles that must be overcome in the different stages of the educational system. If the initial match between available and required human capital is heavily dependent on "signals", workers with higher education diplomas would have a greater chance of being well-matched since their higher education level would be a signal of higher ability and ability is correlated with productivity. However, due to the "democratization" of access to higher education observed in the OECD in the last few decades, there has been an "over-production" of university degrees. Concern has also been expressed about the decline in the quality of university degrees. Gradual drops in educational standards are referred to as "grade inflation", which implies that different qualifications have accrued less human capital over time [20]. Consequently, employers will look for additional filters to fill typical graduate positions among recent higher education graduates. Among the most valued signals would be, for example, the difficulty of the degree obtained (STEM (Science, Technology, Engineering, and Mathematics) vs. non-STEM majors), if the degree was obtained in the scheduled years, the average grade of the academic record, or the reputation of the university from which the degree was obtained [21]. Fresh university graduates who do not possess those signals are more likely to work in traditionally non-graduate jobs, therefore becoming over-educated [22]. After all, employers find themselves with a large pool of candidates from which to choose. Even while the economic theory of "market signaling" acknowledged that education might not always translate into job abilities, companies nevertheless viewed it as an indication that might be associated with more attractive workers [23,24]. Higher education acts as a filtering device to identify the most capable candidates, though other authors also agreed that education increases productivity in addition to signaling [25].

The "job competition model", which was based on Thurow's book *Generating Inequality* [26], also received a lot of attention in the literature on over-education. Thurow's model characterized a labor market within which "individuals compete against one another for job opportunities based on their relative costs of being trained to fill whatever job is considered" [26] (p. 75). The crucial component in this model is that most cognitive job skills are not developed before a worker enters the job market but through on-the-job training programs. To minimize training costs, employers rank potential employees based on their training costs. This leads to the labor queue. Employers rank workers by their background characteristics from those with the lowest training costs to those with the highest training costs; higher educational attainment is an indicator of low training costs. Those workers with the background characteristics that yield the lowest training costs are the first to be offered employment. Thus, college graduates would be the first to be offered employment. However, as the supply of more highly educated labor increases, individuals find that they must expand their own educational qualifications simply to defend their existing position in the queue. Education may, therefore, become a "defensive necessity". Nonetheless, if the distribution of jobs does not change, a larger supply of college workers will force many qualified individuals to accept jobs from the center or lower end of the queue, thus being over-educated. However, so far research has not agreed on which theory best explains the presence of educational mismatch or whether the existence of over-education provides support for a specific theory [27].

The "internal labor markets" (ILMs) argument is another reasonable justification for over-education [28]. ILMs are characterized by well-defined job ladders, entry from the external labor market into "entry-level jobs", and movement of employees up these ladders through promotion once they have acquired firm-specific human capital. The prospect of promotion also serves to motivate employees as they compete to move to positions of higher status and wages. However, one effect of the rise in the number of college-educated workers is that employers may raise the minimum educational standards for entry-level positions above what is required to perform the job satisfactorily, raising concerns about the under-employment of highly educated workers. Nevertheless, according to the theory of ILMs, these over-educated employees will be quickly promoted to higher-level positions as soon as they acquire enterprise-specific abilities (skill specificity), which allow them to improve their education–job match.

2.2. Educational Mismatch among University Graduates: Empirical Evidence

Various procedures have been proposed in the literature to measure the match between formal qualifications and occupations. In applied studies, the measurement of educational mismatch has been based mainly on workers' self-assessments. By asking the respondent to provide information on the minimum educational requirements of the job and then comparing these with the individual's acquired education, educational mismatches are subjectively evaluated. Alternatively, the respondent may be asked whether they believe they are over-educated [8]. Dolton and Vignoles' study [11], which found that 30 percent of 1980 Graduates and Diplomates in the United Kingdom (UK) were over-educated six years after graduation, is one of the earliest studies on vertical mismatch in the job market for graduates based on self-reported information by respondents. A graduate employed in a position requiring sub-degree level qualifications was considered over-educated. In the United States, Ref. [27] looked at the connection between college majors and jobs in order to study the horizontal mismatch. The author showed that 20 percent of the sample stated that their fields of study and jobs were completely unrelated, whereas 55 percent of individuals self-assessed that their jobs and fields of study were closely related. After that, Verhaest et al. used self-evaluations from European graduate surveys to determine the match status five years after graduation [12]. According to the authors, 74.2% of graduates were, on average, well-matched. The average horizontal mismatch incidence was a little over 10%, while it was about 16% in Poland and Estonia and more than 18% in the UK. Most recently, Salas-Velasco showed that 26.2% of Spanish university graduates—prior to the Bologna curriculum reform—were over-qualified four years after graduation (including fully mismatched graduates), while 7.4% were horizontally mismatched [4].

Objective methods, such as statistical methods and job analysis, have also been used for studying the education–occupation mismatch, which is essentially a vertical mismatch. On the one hand, in the statistical method based on the mean, workers who have educational backgrounds that are more than one standard deviation above the mean for their particular occupation are considered over-educated (e.g., [29,30]). On the other hand, the mode-based statistical method classifies an employee as over-educated if their educational attainment is higher than the modal education level of people in their occupation [31,32]. When it comes to job analysis, the educational requirements of various occupational categories are compared to the number of years of education that workers in those occupations actually possess [33]. The educational requirements may be based on an implicit assumption that education and occupations, such as those cataloged by the International Standard Classification of Occupations (ISCO), are related. However, given the complexity of the execution of the objective methods due to the demand for information, we have found no studies in the context of the labor market for graduates.

3. Methods

3.1. Educational Mismatch Measurement: Subjective Self-Assessment

In a simple way, education–occupation mismatch can be defined as the divergence between the formal qualifications that individuals possess and those that are required by jobs. In the graduate job market, we distinguished three educational mismatch statuses. Firstly, when university graduates who were trained in a particular field worked in another field at their formal qualification level (i.e., university graduates who work in graduate jobs unrelated to their degree fields), we labeled their situation "field-of-study mismatch" or "horizontal mismatch". Secondly, when university graduates worked in jobs that require sub-degree-level qualifications, but the jobs were somehow related to their degree fields, we labeled their situation "over-education" or "vertical mismatch". The third scenario involved college graduates who were employed in non-graduate employment unrelated to their degree fields. This circumstance could be described as "full mismatch" (i.e., field-of-study mismatch and over-education). We should highlight that under-education was not possible when the attention was on higher education graduates, while vertical mismatch had the same connotation as over-education or over-qualification. Vertical mismatch, however, was a more limited term in this article's analysis because it only included graduates who were employed in jobs that were linked to their fields of study but did not require a university degree.

Methodologically, these mismatch statuses presented problems of measurement. The most straightforward way to measure educational mismatch was to ask everyone to evaluate themselves. In other words, an educational mismatch could be evaluated subjectively by asking the respondent to offer details on the minimum educational requirements of the position and then comparing those details with the individual's actual education. In addition, respondents were asked how closely their field of study relates to the employment they held. Self-assessment methods may have been biased since they depend on respondents' impartiality; however, objective measures, such as job analysis, are also controversial because there is not a fixed 1:1 relationship between most jobs and particular educational levels. In the study of the relationships between education and employment, it was almost impossible, in practice, to assign an educational level to the jobs in the economy since the contents of the jobs (tasks to be performed) were defined differently depending on the type of company (size, sector in which it operates, etc.). Moreover, an objective approach would be too complex to measure the horizontal mismatch in the graduate labor market.

Thus, measures of subjective self-assessment were used in this study to define an adequate match, horizontal mismatch, vertical mismatch, and full mismatch. In the EILU2019 survey, the 2014 graduation cohort informed us, at the time of the interview in 2019, whether or not their current positions needed a university degree and what was the most appropriate study area (field of education) for these positions. In order to evaluate if a job required a degree, the following questionnaire question was asked: Q1 = which educational level would be most suited to carry out this work? Respondents could choose between the following levels of education: A1 = a university degree; A2 = vocational post-secondary education; A3 = a diploma from high school; and A4 = middle school. A separate question asked respondents about the (un)relatedness of a worker's field of study to his or her occupation: Q2 = what do you think is the most appropriate study area for this work? This question was followed by a choice of four options: B1 = exclusively the area of studies of my degree; B2 = some related areas; B3 = a totally different area; and B4 = no particular area.

Following Salas-Velasco's methodological paper [4], we first classified undergraduate degree holders as well-matched if individuals responded with A1 and either B1 or B2 (i.e., an occupation that both requires a university degree and is directly related to the respondent's area of specialization). Secondly, the horizontal educational mismatch was identified when an occupation required a university degree but was not directly connected to the training provided by the degree, that is, whether they gave the answers A1 and either B3 or B4. Thirdly, when a job did not require a university degree but the field of study was relevant to the position, the educational mismatch was categorized as vertical, that is, if respondents answered A2, A3, or A4 and B1 or B2. Finally, vertical and horizontal mismatch (full mismatch) was identified when a job did not require a university degree and was unrelated to the respondent's field of study; this was the case when workers answered A2, A3, or A4 and B3 or B4. By using both dimensions as defining axes (i.e., graduate vs. non-graduate jobs and specific vs. general human capital), we could make a sound choice of distinguishing concepts, as depicted in Figure 1. On the vertical axis, we could determine whether respondents were working below their own level (i.e., those whose level of university education was not necessary to perform their job). On the horizontal axis, the focus was on match quality in terms of fields of study, which could be understood as different stocks of human capital differentially valued by employers. Some fields of study entailed a high degree of specialization (specific human capital), while others were less specific, leading to a wider range of occupations (general human capital). Figure 1 provides some examples of how we classified each type of job match for four different bachelor's degree holders.

Incidence of Educational Mismatch

In 2019, 86.1% of undergraduates who graduated from the Spanish university system in the 2013/2014 academic year were working (approximately 10% of those were self-employed), 8.0% were unemployed, and 6.4% were inactive [34]. Table 1 shows the proportion of salaried workers (i.e., excluding the self-employed) who were properly matched, as well as in each of the three mismatch categories, five years after graduation. Looking at the incidences in Table 1, 67.3% of the graduates reported being adequately matched in their current jobs in terms of their formal (and type of) university education, while 11.2% of them were horizontally mismatched. However, 21.5% of Spanish graduates were in non-graduate jobs, indicating that they were over-qualified (i.e., the percentage of degree holders in occupations that do not require degrees). Approximately 7% of respondents were vertically mismatched, while 15% were both vertically and horizontally mismatched (Table 1).

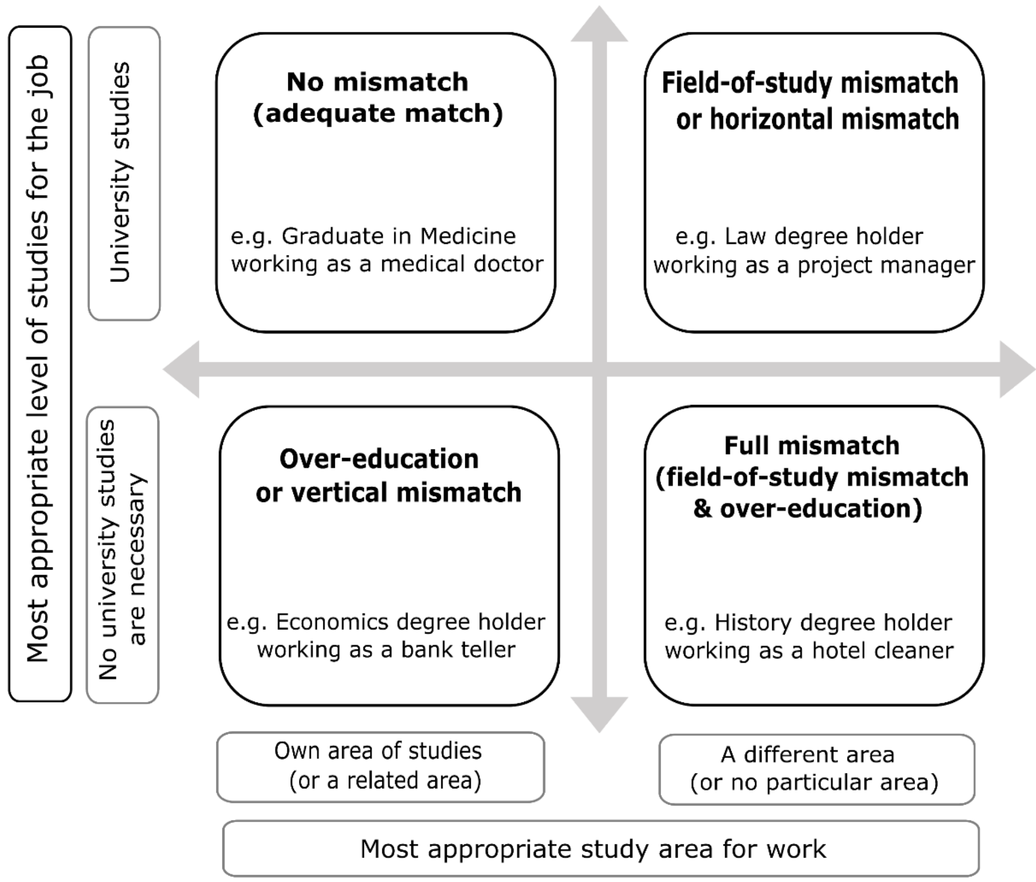

Figure 1. Two dimensions of labor market matching from a university degree perspective. Source: adapted from Salas-Velasco [4] and own elaboration.

Table 1. Incidence of educational (mis)match in graduate labor market: the case of Spain [(a)].

	Current Job in 2014 (EILU2014 Survey) [(b)]		**Current Job in 2019 (EILU2019 Survey)** [(c)]	
	Freq.	**Percent**	**Freq.**	**Percent**
Educational (mis)match				
No mismatch	12,387	66.38	16,395	67.29
Horizontal mismatch	1379	7.39	2735	11.23
Vertical mismatch	1725	9.24	1655	6.79
Vertical and horizontal mismatch	3169	16.98	3580	14.69
Total	18,660	100.00	24,365	100.00

[(a)] Both sub-samples include only wage-earners. [(b)] Spanish university graduates from class of 2010, surveyed four years after graduation. [(c)] Spanish bachelor’s degree holders who graduated in 2013/2014 academic year. Source: author’s calculations.

The incidence of horizontal, vertical, and full mismatches using the first Spanish graduate survey (EILU2014) is also presented in Table 1 (measures of educational mismatch are the same in both waves, but degrees are not totally comparable). The 2019 cohort had greater success in matching their qualifications to a job than the 2014 cohort: 67.3% and 66.4% of graduates of both genders were in jobs that required a degree, respectively. This result is reasonable since the 2019 cohort was interviewed five years after graduation, while the 2014 cohort was interviewed four years after graduation. Moreover, the macroeconomic environment (e.g., the unemployment rate) was much more favorable for the 2019 cohort. Fluctuations in the business cycle were expected to have an impact on the likelihood of being employed in a non-matching job. However, in general the incidence of educational mismatch seems not to have changed significantly in the labor market of Spanish university graduates, with around one-third of graduates being mismatched.

According to economic theories of a dynamic labor market, there will always be some degree of mismatch between educational achievements and job requirements; the normal adjustments of a functioning labor market should operate to reduce imbalances as they appear [35]. However, the results shown in Table 1 suggest that there are structural and job characteristics of the Spanish graduate labor market that may affect the matching process since the proportion of degree holders in mismatched jobs is similar in both cohorts. In this regard, it is necessary to highlight the business dimension of Spanish firms: 95.5% of Spanish companies had fewer than 10 workers (as of 1 January 2020). In small firms, an education–occupation match could barely be achieved even several years after earning a degree when workers have already acquired labor market skills and/or have learned to perform a more effective job search. In such a business environment, mismatch may be interpreted as an equilibrium phenomenon [36], though there are no studies providing estimates of what constitutes an optimal amount of graduate mismatch and how much, therefore, might be too much [35].

3.2. Modeling the Education–Job Match

Inspection of the information in Table 1 reveals that educational mismatch was a significant phenomenon in the labor market for university graduates in Spain. Many graduates of higher education hold jobs that did not require a university degree and/or did not fit their specialties. However, this article went beyond showing the incidence of educational mismatch among wage-earners and tried to identify which degrees were more likely to fall in each of the four quadrangles in Figure 1, once controlled for individual socio-demographic characteristics. Since all possible educational match/mismatch statuses were included, which were disjoint and had an order irrelevant for the analysis, a suitable estimation technique was offered by the multinomial logit model, also known as multinomial logistic regression.

3.2.1. The Econometric Model

The multinomial logit model has its foundations in the theory of individual choice behavior. Following McFadden [37], consider an individual who has J alternatives, indexed $j = 1, \ldots, J$ and described by a vector of observed attributes x_j for each alternative. The individual has a utility function, which can be written in the form: $U = V(x) + \varepsilon(x)$, where V is non-stochastic, ε is stochastic.

The probability that an individual will choose the alternative i equals

$$P_i = \text{Prob}\ [V(x_i) + \varepsilon(x_i) > V(x_j) + \varepsilon(x_j) \text{ for all } j \neq i]. \tag{1}$$

Statistical analysis of models with qualitative dependent variables can be viewed as the problem of predicting probabilities for the various possible values (responses) of the dependent variable [38]. For example, according to McFadden [37], the choice probability for alternative 1 is:

$$P_1 = \frac{e^{V_1}}{\sum_{j=1}^{J} e^{V_j}} \tag{2}$$

3.2.2. A Multinomial Logit Model of the Probability of Education–Employment Matching

This sub-section applies the above framework to the graduate labor market by estimating a multinomial logit model of job matching. We started from the assumption that wage-earners accept jobs for which they are well-matched and reject others for which they are poorly matched, though they may finally accept the latter if their expectations of obtaining a suitable job are not realized. Furthermore, since job searching is costly, workers may optimize by accepting an offer for a job that requires less education than they possess [39]. Others may purposefully accept positions unrelated to their education if they value the non-monetary characteristics of the jobs more (e.g., flexibility in working hours, proximity to relatives' homes, etc.); other important characteristics include the availability of on-the-job training and the prospect of being promoted. Some may even switch to self-employment as a way to achieve a job match. However, the mismatch outcome also depends on choice and opportunity, that is, the matching process is also influenced by the structure of the labor market, the productive model of the economy, and the business cycle. Nevertheless, graduate surveys rarely provide economists with information about the labor market matching process, that is, how individuals ended up in one of the four quadrants depicted in Figure 1. However, it is to be expected that, after five years in the labor market, there would be an "equilibrium" in the allocation of individuals to jobs in each quadrant based on observable characteristics (e.g., formal human capital) as well as unobservable individual traits (not recorded in the data and accordingly unobserved by the econometrician). In other words, the 2014 Spanish university graduates had five years to enhance the match between their degree and job. Thus, the mismatch outcome observed in 2019 was an employment status that the individual had accepted (chosen) in some way.

We assumed that preferences are such that all occupations have a positive selection probability for each individual. Thus, a multinomial logit model (MLM) could be used to estimate the probability that the different degrees awarded by Spanish universities after the Bologna reform fell into each of the four quadrants of Figure 1. The MLM, or multinomial (polytomous) logistic regression model, is a generalization of the binary model when the outcome variable is categorical with more than two nominal (unordered) values. In the current study, the response variable had four categorical outcomes, which did not have an ordered structure: appropriate match (no mismatch), horizontal mismatch, vertical mismatch, and vertical and horizontal mismatch (j = 1, 2, 3, 4, respectively). The MLM considered the probability of a certain event j as [40]:

$$prob(Y = j) = exp\left(x'\beta_j\right) / \sum_{k=1}^{4} exp\left(x'\beta_k\right) \tag{3}$$

Model (3) gave the probability that an individual with specific characteristics x was in group j. In this paper, the explanatory variables of interest were mainly the new university degrees. The natural normalization is $\beta_4 = 0$, with the probability of jth outcome defined as:

$$prob(Y = j) = \frac{exp\left(x'\beta_j\right)}{1 + \sum_{k=1}^{3} exp(x'\beta_k)}, \quad if\ j = 1, 2, 3 \tag{4}$$

And for the baseline category (vertical and horizontal mismatch).

$$prob(Y = 4) = \frac{1}{1 + \sum_{k=1}^{3} exp(x'\beta_k)}, \quad if\ j = 4 \tag{5}$$

Nevertheless, we also had to compute marginal effects to make meaningful inferences regarding the direction and strength of the link between an independent and dependent variable in an MLM [41]. The marginal effects informed us of the change in predicted probabilities resulting from a change in a particular predictor.

3.2.3. Estimation Results

As mentioned, in order to examine the effects of different post-Bologna degrees on the educational mismatch under ceteris paribus conditions, a multinomial logit model has been estimated. Table 2 presents the estimated average marginal effects (AME) from the estimated coefficients of the MLM along with the standard errors. The bachelor's degrees granted by the Spanish university system following the Bologna reform were introduced by degree dummies. Up to 101 different bachelor's degree programs (specific fields of study) were included in the EILU2019 survey; for the analysis, these programs were grouped into 44 categories (narrow fields of study). Journalism was selected as the category for comparison because its graduation rate (around 2.3% of the sample) is equal to the overall mean. In addition to the degrees awarded by the Spanish universities, the model included, for the current job, pre-hire controls on workers' socio-demographic characteristics and job requirements.

Results displayed in Table 2 indicate that, in general, university graduates from highly specialized programs were more likely to work at a graduate job that is related to their field of education. In particular, graduates with degrees that entail specific human capital, such as health sciences degrees along with hard science and engineering degrees (STEM degrees), are more likely to be well-matched in their current jobs (estimated average marginal effects that were positive and statistically significant). For example, graduates with degrees in odontology, medicine, nursing, veterinary, physiotherapy, and pharmacy had the highest likelihood of achieving an education–job match five years after graduation. These results point to high-skilled workers' limited human capital transferability. They were qualified only for jobs within their own profession and were, thus, employed in a highly specialized labor market. Our estimates indicate, for instance, that those who graduated in Medicine had an increased average probability of being well-matched by 0.641 (i.e., medical doctors were on average about 64% more likely than journalists to have a positive adequate match outcome). Among the STEM degrees, for example, a degree in Computing was associated with a 20% increase in the probability of being well-matched in their current job five years after graduation. This probability also increased significantly if the graduate was a physicist (about 19 percentage points), engineer (about 17 percentage points), or mathematician (about 11 percentage points). All of these graduates were more likely to work in a graduate job that was directly related to their field of study in order to use specific human capital that was accrued during university studies. These results for well-matched graduates are in line with the results found by Salas-Velasco [4], who looked specifically at Spanish university graduates from the class of 2010 who were working in 2014.

In contrast, general study programs offer a wider array of skills that can be used across occupations. In particular, this study finds that graduates in humanities and social sciences degrees, such as geography and history, sociology, political sciences, and philosophy, had an increased probability of being horizontally mismatched (Table 2). The degree to which people, typically graduates, are in a profession unrelated to their primary field of study is known as horizontal mismatch [42]. For example, graduating in sociology increased the average probability of being horizontally mismatched by 0.067 (i.e., sociologists are on average about 7% more likely than journalists to have a positive horizontal mismatch outcome). While general human capital may be included in this situation, a horizontal mismatch may find it more difficult to support any specific human capital that is included in a particular sort of qualification. Empirical evidence reveals that, among other factors, the degree to which employees acquire generic skills, as opposed to occupation-specific abilities, determines the chance of horizontal mismatch or field-of-study mismatch [10]. However, even if a degree program is not directly vocational, it is still likely to develop student capabilities that are entirely relevant to the work situation, such as critical analysis, problem-solving, teamwork, and presentation skills. The abilities that these majors typically offer are more general than profession-specific [27].

Table 2. Multinomial logit model of probability of being (mis)matched five years after graduation: estimated average marginal effects [(a)].

	Pr (Jobmatch = 1) No Mismatch			Pr (Jobmatch = 2) Horizontal Mismatch			Pr (Jobmatch = 3) Vertical Mismatch			Pr (Jobmatch = 4) Vertical and Horizontal Mismatch		
	dy/dx		Std. Err.	dy/dx		Std. Err.	dy/dx		Std. Err.	dy/dx		Std. Err.
Bachelor's degree awarded [(1)]												
Educational Studies	0.094	***	0.022	−0.050		0.018	−0.007		0.015	−0.037		0.015
Teaching	0.103	***	0.018	−0.067		0.014	0.011		0.012	−0.047		0.012
Fine Arts [(2)]	−0.132		0.020	0.032	**	0.014	0.050	***	0.013	0.050	***	0.013
Geography and History [(3)]	−0.117		0.026	0.074	***	0.016	−0.061		0.024	0.103	***	0.015
Philosophy	−0.089		0.036	0.046	**	0.021	−0.042		0.033	0.084	***	0.021
Foreign Languages [(4)]	−0.046		0.026	0.036	**	0.016	−0.026		0.022	0.036	**	0.018
Language and Literature	0.047		0.030	−0.020		0.020	−0.064		0.030	0.038	**	0.019
Economics	0.022		0.022	−0.007		0.016	0.053	***	0.014	−0.068		0.016
Political Sciences	−0.157		0.028	0.064	***	0.018	0.054	***	0.016	0.039	**	0.019
Psychology [(5)]	−0.006		0.021	0.001		0.016	0.001		0.015	0.004		0.015
Sociology	−0.109		0.042	0.067	***	0.026	0.027		0.026	0.015		0.027
Finance and Accounting	0.096	***	0.035	−0.044		0.028	0.026		0.020	−0.078		0.025
Business Administration	0.058	***	0.019	−0.038		0.014	0.059	***	0.012	−0.079		0.013
Labor Relations	0.015		0.027	−0.028		0.021	0.017		0.017	−0.005		0.018
Marketing	−0.038		0.024	0.029		0.016	0.042	***	0.015	−0.033		0.017
Law	−0.007		0.020	0.000		0.014	0.032	**	0.013	−0.025		0.014
Biology	−0.008		0.026	−0.035		0.020	0.051	***	0.015	−0.008		0.018
Biomedical and Health Engineering [(6)]	0.096	***	0.029	−0.010		0.020	−0.002		0.022	−0.084		0.025
Environmental Sciences	−0.079		0.025	0.057	***	0.016	0.016		0.017	0.006		0.017
Chemistry	0.030		0.027	−0.021		0.021	0.057	***	0.016	−0.065		0.022
Geology [(7)]	−0.072		0.029	0.016		0.021	0.010		0.021	0.046	**	0.019
Physics [(8)]	0.188	***	0.041	0.008		0.022	−0.106		0.045	−0.090		0.030
Mathematics and Statistics	0.111	***	0.027	−0.018		0.020	−0.006		0.019	−0.087		0.021
Computing	0.200	***	0.022	−0.100		0.018	0.042	***	0.013	−0.143		0.018
Chemical Engineering	0.064		0.036	0.042		0.022	−0.025		0.030	−0.082		0.027
Electric Engineering [(9)]	0.176	***	0.034	−0.012		0.023	−0.012		0.024	−0.151		0.030
Telecom Engineering	0.170	***	0.023	−0.048		0.017	0.031	**	0.014	−0.152		0.019
Industrial Engineering	0.163	***	0.021	−0.034		0.015	0.013		0.014	−0.142		0.017
Naval and Aeronautical Engineering	0.178	***	0.035	−0.018		0.023	−0.002		0.024	−0.158		0.032
Food Engineering [(10)]	0.052		0.033	0.024		0.022	0.031		0.020	−0.106		0.030
Civil Engineering [(11)]	0.089	***	0.022	0.019		0.015	−0.033		0.017	−0.075		0.016
Architecture	0.072	***	0.022	−0.021		0.016	−0.009		0.016	−0.042		0.016
Agricultural Engineering [(12)]	0.054	**	0.022	−0.021		0.016	0.014		0.014	−0.047		0.016

Table 2. *Cont.*

	Pr (Jobmatch = 1) No Mismatch			Pr (Jobmatch = 2) Horizontal Mismatch			Pr (Jobmatch = 3) Vertical Mismatch			Pr (Jobmatch = 4) Vertical and Horizontal Mismatch		
	dy/dx		Std. Err.	dy/dx		Std. Err.	dy/dx		Std. Err.	dy/dx		Std. Err.
Veterinary	0.312	***	0.042	−0.089		0.031	−0.131		0.045	−0.093		0.027
Odontology	1.715	***	0.066	0.308	***	0.069	−0.758		0.023	−1.265		0.033
Medicine	0.641	***	0.061	−0.200		0.051	−0.090		0.034	−0.351		0.069
Nursing	0.413	***	0.028	−0.081		0.020	−0.064		0.019	−0.268		0.027
Physiotherapy	0.216	***	0.031	−0.028		0.023	−0.079		0.027	−0.109		0.024
Pharmacy (13)	0.211	***	0.033	−0.054		0.025	−0.042		0.024	−0.115		0.025
Social Work	0.093	***	0.023	−0.075		0.019	0.005		0.014	−0.023		0.015
Sports Science	−0.031		0.025	−0.029		0.020	0.045	***	0.015	0.016		0.017
Tourism	−0.126		0.025	0.013		0.017	0.092	***	0.014	0.021		0.016
Transport and Services	0.046		0.034	0.011		0.023	0.039		0.020	−0.096		0.029
Factors to find the job: theory (b)	0.194	***	0.005	−0.031		0.004	−0.015		0.003	−0.148		0.004
Factors to find the job: practical skills	0.106	***	0.006	−0.029		0.004	0.009	**	0.004	−0.086		0.004
Factors to find the job: knowing languages	0.050	***	0.006	0.032	***	0.004	−0.037		0.004	−0.045		0.005
Factors to find the job: computer skills	0.010		0.006	0.023	***	0.004	−0.002		0.003	−0.031		0.005
Factors to find the job: management ability	0.073	***	0.007	0.016	***	0.005	−0.019		0.004	−0.069		0.005
Factors to find the job: personal and social skills	−0.031		0.008	0.007		0.006	0.001		0.005	0.022	***	0.006
Double university degree (=1 yes)	0.073	***	0.014	0.024	***	0.009	−0.033		0.010	−0.065		0.013
Master's degree (=1 yes)	0.092	***	0.006	0.008		0.004	−0.035		0.004	−0.064		0.004
Age under 30 years (c)	0.059	***	0.007	−0.015		0.005	−0.013		0.004	−0.030		0.005
Age of 35 or more years	−0.033		0.008	0.050	***	0.005	−0.006		0.004	−0.011		0.006
Private university (=1 yes)	0.045	***	0.009	0.008		0.006	−0.001		0.005	−0.052		0.007
Gender (=1 male)	0.003		0.006	0.008		0.004	−0.008		0.003	−0.003		0.004

(1) The reference category was Journalism (Communication, and Information and Documentation were also included). (2) This category also included History of Art and Conservation and Restoration. (3) This category also included Anthropology. (4) This category also included Translation and Interpreting. (5) This category also included Speech Therapy. (6) This category also included Biochemistry, Biotechnology, and Biomedicine. (7) This category also included Archeology. (8) This category also included Optics and Optometry. (9) This category also included Energy Engineering. (10) This category also included Science and Technology of Food and Oenology. (11) This category also included Mining Engineering. (12) This category also included Forest Engineering. (13) This category also included Human Nutrition and Diet. (a) Only wage-earners workers. (b) The six variables listed below are binary. The variable takes the value of 1 if it was an important or very important factor in obtaining the current job; it takes the value of 0 otherwise. (c) Age group (as of 31 December 2019). Reference category: from 30 to 34 years. Dependent variable: *jobmatch*. Standard errors for average marginal effects are computed by the Stata *margins* command using the Delta method. Model VCE: robust. Number of obs. = 24,365. Except for rounding errors, the sum of marginal effects for four categories must be 0. Wald chi2(165) = 14,685.96; Prob > chi2 = $p < 0.001$. Pseudo R2 = 0.180. Log pseudo-likelihood = −19,510.23. Goodness-of-fit test for a multinomial logistic regression model: A generalized Hosmer–Lemeshow goodness-of-fit test under the null hypothesis that fitted model is the correct model; number of groups = 10, chi-squared statistic = 16.701, degrees of freedom = 24, Prob > chi-squared = 0.861. Marginal effects that have a positive and statistically significant contribution to probability of being well-matched or mismatched in current job: *** Significant at the 1% significance level, ** significant at the 5% significance level. Source: author's estimates using Stata 17® software.

The results also show a higher likelihood of over-qualification for graduates who possess degrees in social and legal sciences and arts and humanities. Among the former group, degrees in tourism, business administration, economics, marketing, and law increased the likelihood of vertical mismatch (over-education in a narrow sense). This mismatch between education and employment may be due to the "excessive" production of business and economics graduates in Spanish universities. In general, imbalances between supply and demand in terms of fields of study are also likely to explain mismatches. Among the latter group, degrees such as fine arts, language and literature, and foreign languages have the highest likelihood of a full mismatch (i.e., those working in non-graduate-level jobs and fields unrelated to their education). For instance, finishing language and literature is linked to a 0.038 rise in the average likelihood of being doubly mismatched (Table 2). Nonetheless, a vertical mismatch preserves at least some of the specific human capital acquired through higher education, unlike a full mismatch. Figure 2 summarizes the main results. In each category of the dependent variable (i.e., the various mismatch statuses), the degrees have been ordered from the highest to lowest estimated marginal effects that are statistically significant.

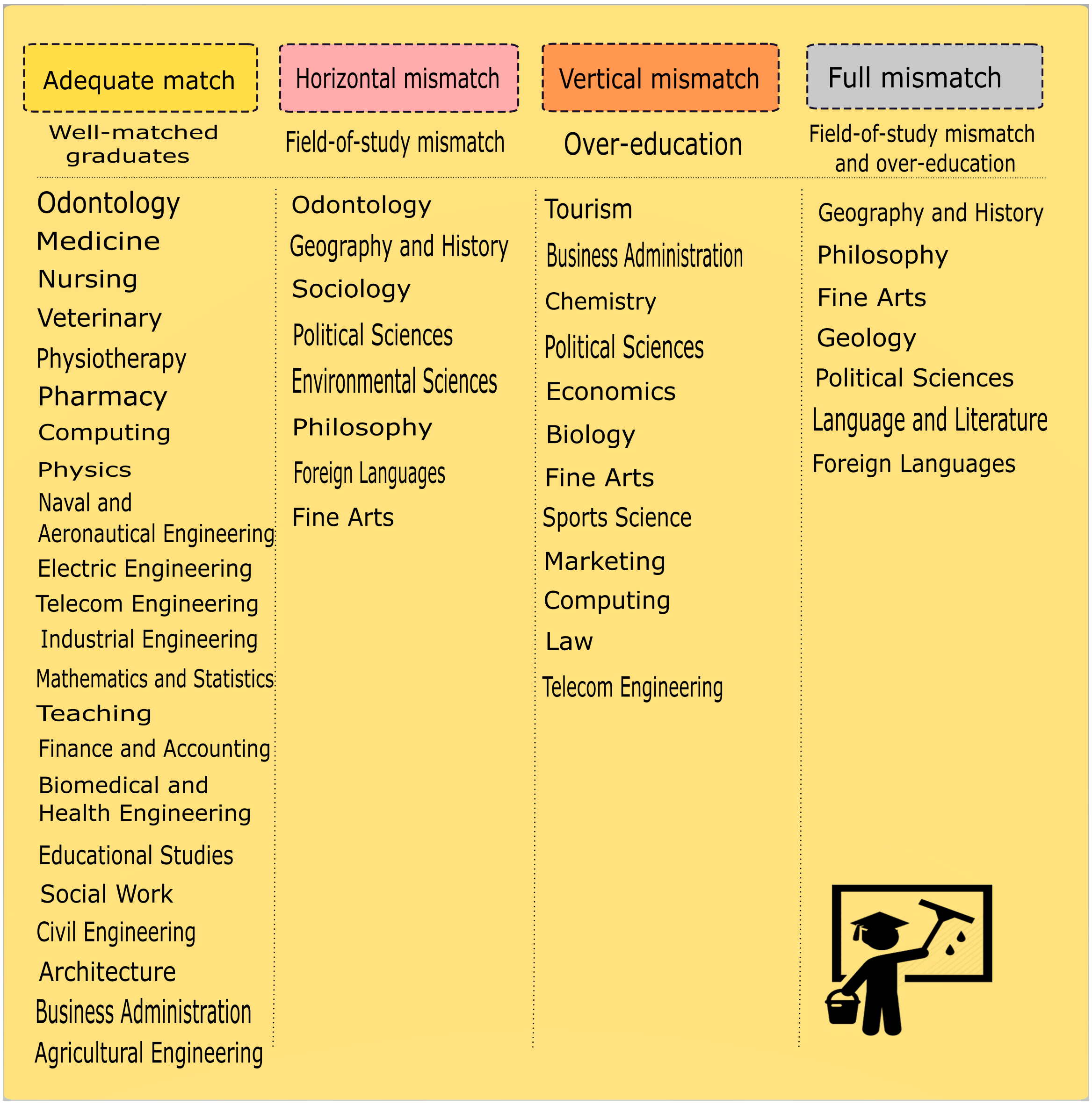

Figure 2. The reform of curricula in Spanish university system through lens of education–job mismatch in graduate labor market. Source: author's elaboration.

In addition to the results shown above, other results were briefly considered in this subsection. Firstly, graduates' ages had an impact on the likelihood of being mismatched. The average probability of being well-matched in the current work increased by 0.059 in people under 30 (Table 2). In contrast, graduates 35 years of age or older had a higher likelihood of being horizontally mismatched. The literature also revealed this outcome [10]. Secondly, the probability of an education–job match increased if the degree was earned at a private university. Thirdly, undergraduates who have completed a master's degree had a higher likelihood of achieving a good match five years after graduation. Additional post-college educational credentials may have had the purpose of signaling the level of the worker's productivity to potential employers who have only imperfect information. Fourthly, this probability also increased appreciably if "theory" was an important or very important factor in obtaining the current job. This result once again suggests that the relative specificity of college majors was associated with a greater likelihood of being well-matched. In some cases (for example, medicine and engineering), the subject-specific knowledge and understanding that graduates gained from their time in higher education were important [3]. Lastly, gender appears to have played no role in the matching process, contradicting past studies that found that female college graduates have a higher likelihood of being in jobs for which they are over-qualified than comparable men (e.g., [12,43]).

Finally, we observed that some degrees increased the probability of being in two squares of educational (mis)match, as shown in Figure 1. This mismatch status difference was partially attributed to the ability heterogeneity among equally-educated individuals, who face intense competition for limited high-skilled jobs within their field-of-study segment of the labor market. For example, in Figure 2, individuals graduating from a relatively general study program, such as philosophy, geography and history, or political sciences, had an increased probability of being both horizontally and fully mismatched five years after graduation. Graduates with an arts degree are more likely to experience any type of mismatch. Nonetheless, due to data limitations, the role that ability and other unobserved individual traits played in the matching process remains to be tested. Indeed, addressing the endogeneity problem resulting from unobserved heterogeneity is still an unsolved issue in the applied literature on educational mismatch.

3.2.4. Tests for the Multinomial Logistic Regression Model

For the global contrast of the estimated model, the Chi-square test was used. The null hypothesis was that all the coefficients of the equation, except the constant, were null. In particular (Table 2), Wald chi2 (165) = 14,685.96, and the associated *p*-value was very low (less than 0.001). The result of this test allowed one to reject the null hypothesis. For evaluating the "goodness-of-fit of the model" in regression models with categorical dependent variables, the literature proposes the so-called pseudo-R2 measures. A measure of goodness-of-fit is a "summary statistic" that indicates the precision with which a model approximates the observed data. The pseudo-R2 proposed by McFadden [37] was 0.180. This result led one to think that, being a low value, the explanatory capacity of the model was low. However, when working with qualitative response models, it was not easy to interpret values of R2 between 0 and 1; in these cases, the maximum value of R2 was much lower than 1, unlike the case with a linear model [44]. Furthermore, we can see at the bottom of Table 2 that the Hosmer–Lemeshow test is not significant, meaning that the multinomial logistic regression model suitably fits our data [45]. Finally, we checked for the "independence of irrelevant alternatives" (IIA) assumption. This assumption asserts that the choice of or membership in one category was not related to the choice of or membership in another category (i.e., the dependent variable). The IIA assumption could be tested via the Hausman–McFadden test [46]:

H_0: Odds (outcome-J vs. outcome-K) were independent of other alternatives.

Evidence for H_0 was found for omitted 1, 2, 3, and 4. Results are not shown, but they are available upon request from the corresponding author.

4. The Education–job Matching Process

In the previous section, we discovered that, five years after graduation, STEM-related and health sciences degrees are primarily those university credentials that, all else being equal, show a good match with jobs. These graduates hold positions in which they optimize their investments in formal human capital, that is, they work in graduate jobs related to their area of specialization and, therefore, it is expected that they maximize lifetime earnings. However, a relatively neglected area of research in labor economics is the job-matching process. The matching of workers' knowledge and skills with job requirements is a complex process where factors at the individual, organizational, and institutional levels influence employment outcomes. Although our empirical model included a wide range of formal qualifications and controls for individuals' and jobs' characteristics, the presence of other unobserved factors that are correlated with the likelihood of job matching remains a possibility. If this is the case, our logit estimates might be biased. In order to take job self-selection into account, we considered the following question posed in the EILU2019 survey: *Since you graduated, have you rejected any job because you considered it unsuitable?* If yes, respondents had a variety of options from which to choose. We are interested in estimating the probability of achieving a good match for the sub-sample of graduates who previously self-selected by rejecting job offers they considered inadequate in salary or training. We restricted the analysis to wage-earners who had had a single employer since graduation. This analysis was based on the hypothesis that an adequate match is the outcome of a self-selection process by the individuals that, finally, led them to the status reported in the survey. As an estimation method, a binomial probit model with sample selection was used.

4.1. A Binomial Probit Model with Sample Selection

For binary outcome y_i and regressors $\boldsymbol{x}_i$, the probit model assumes [47]:

$$y_i = \mathbf{1}(\boldsymbol{x}_i\boldsymbol{\beta} + \epsilon_i > 0) \tag{6}$$

where the error ϵ_i is standard normal. The indicator function $\mathbf{1}(\cdot)$ outputs 1 when its input is true and outputs 0 otherwise.

Ref. [48] presented the probit model with sample selection to account for consistent estimation of $\boldsymbol{\beta}$ in samples that suffer from the selection on unobservables. The equation for the outcome (6) remains the same, though another equation is added. The selection process for the outcome is modeled as [47]:

$$s_i = \mathbf{1}(\boldsymbol{z}_i\boldsymbol{\gamma} + \epsilon_{si} > 0) \tag{7}$$

where $s_i = \mathbf{1}$ if we observed y_i and $s_i = 0$ otherwise, while $\boldsymbol{z}_i$ are regressors that affect the selection process.

The errors ϵ_i and ϵ_{si} are assumed to be standard normal with:

$$\mathrm{corr}(\epsilon_i, \epsilon_{si}) = \rho$$

"rho" is bound between -1 and 1; it is the correlation between the outcome equation and the selection equation. Test of H_0: rho = 0; under H_0, there is no sample selection problem. When $\rho \neq 0$, the usual OLS standard errors are not exactly correct [49].

The Heckman-type correction [50] described is a well-known two-step statistical approach in the presence of the non-random assignment of individuals to two different statuses. Firstly, we can estimate $\boldsymbol{\gamma}$ by probit of s_i on $\boldsymbol{z}_i$, using the entire sample. In the second step, we can estimate $\boldsymbol{\beta}$. In the analysis, $\boldsymbol{x}$ should be a strict subset of $\boldsymbol{z}$. Thus, any element that appears as an explanatory variable in Equation (6) should also be an explanatory variable in the selection for Equation (7). However, at least one element of $\boldsymbol{z}$ is not also in $\boldsymbol{x}$. This means that we need at least one variable that affects selection but does not have a partial effect on y. In short, one must identify such an extra variable, known as an *exclusion restriction* [49].

4.2. Estimation Results

This research, in the first stage, used a probit model to estimate the participation equation that determines the decision to reject a job because it is considered inappropriate since it does not match the training and salary expectations of the respondent: yes = 1 (581 individuals); no = 0 (6352 individuals). Specifically, the "1" included those who answered "yes" to that question (in italics) and stated that the main reason for rejecting the job was that the job level did not match their skills and knowledge or the job was not adequately remunerated. Since education and earnings are highly correlated, individuals sought jobs whose educational requirements match their educational attainment. The "0" included both those who answered "no" to the question posed (in italics) and those who answered "yes" for different reasons not related to training or salary. In the second stage, for the sub-sample of the "yes" observations, we estimated the probability of having achieved a good match (1 = yes, 0 = no), using a probit model (match outcome =1 for about 70 percent of the sub-sample).

The estimation results are shown in Table 3. Because of the significant reduction in the number of observations, the degrees were classified into four broad categories. The degrees in social sciences and law were specifically excluded (reference category). The estimated coefficients of the outcome equation for STEM and health sciences degrees were positive and statistically significant once sample selection was taken into consideration. The previous result was confirmed again, that is, STEM and health sciences degree holders had an increased the probability of being well-matched. The predicted value for "rho" stands out in the results shown in Table 3, which turned out to be significantly different from 0, showing the problem of sample selection (the null hypothesis was rejected). Accounting for sample selection was, therefore, necessary to obtain correct parameter estimates and statistical significance. Finally, as we anticipated, in the econometric estimation at least one of the explanatory variables should influence the likelihood of selection (i.e., having rejected a job considered inadequate in salary or training) but not affect the outcome (i.e., the likelihood of matching). In the analysis, two variables were excluded in the second stage: whether the graduate does not have a disability and the educational level of the mother, which affected the probability of selection (Table 3). These two variables did not affect the probability of achieving a good match. Results are not shown, but they are available upon request from the corresponding author.

Table 3. Probability of achieving an education–job match: Probit model with sample selection.

	First Stage: Participation Equation (Probit)			Second Stage: Outcome Equation (Probit)		
	Coef.		**Robust Std. Err.**	**Coef.**		**Robust Std. Err.**
Arts and humanities degrees	−0.009		0.083	−0.262	**	0.108
STEM degrees [(a)]	−0.013		0.052	0.252	***	0.088
Health sciences degrees	−0.100		0.073	0.304	**	0.130
Factors to find the job: theory [(b)]	−0.195	***	0.049	0.419	***	0.076
Factors to find the job: practical skills	−0.058		0.055	0.231	***	0.086
Factors to find the job: knowing languages	0.140	***	0.052	−0.092		0.078
Factors to find the job: computer skills	0.146	***	0.051	−0.224	***	0.085
Factors to find the job: management ability	−0.030		0.063	0.221	**	0.088
Factors to find the job: personal and social skills	0.112		0.066	−0.463	***	0.110
Double university degree (=1 yes)	0.341	***	0.103	−0.075		0.173
Master’s degree (=1 yes)	0.179	***	0.047	0.009		0.077
Age under 30 years [(c)]	0.029		0.062	−0.113		0.098
Age of 35 or more years	−0.072		0.059	−0.050		0.091
Private university (=1 yes)	−0.001		0.063	0.404	***	0.129
Gender (=1 male)	0.216	***	0.046	−0.257	***	0.070
Recognized disability [(d)]	0.325	**	0.163			
Mother with a university education (=1 yes)	0.089	**	0.045			
Constant	−1.910	***	0.178	2.046		0.099
Log pseudolikelihood = −2226.32	Number of obs. = 6933			Number of obs. = 581		
rho = −0.997 [95% Conf. Interval: −1.00, −0.83]						
Wald test of indep. eqns. (rho = 0): chi2(1) = 9.55 Prob > chi2 = 0.002						
Wald chi2(15) = 113.13 Prob > chi2 = $p < 0.001$						

[(a)] Hard science and engineering degrees (also architecture) have been included in STEM degrees. [(b)] The six variables listed below are binary. The variable takes the value of 1 if it was an important or very important factor in obtaining the current job; it takes the value of 0 otherwise. [(c)] Age group (as of 31 December 2019). Reference category: from 30 to 34 years. [(d)] = 1: graduate has no recognized disability; =0: graduate has a recognized disability of more than 33%. *** Significant at the 1% significance level, ** significant at the 5% significance level. Source: author’s estimates using Stata 17® software.

5. Discussion

The extent to which workers are matched to jobs is a hotly debated topic in countries such as Spain, where job titles, in general, are defined in terms of educational requirements that coincide with the levels and types of formal education. Most of the empirical literature on worker–job fit has focused on the mismatch between the formal education possessed by a worker and the one required for the job. From an overall economic perspective, if such mismatches occur, the available human capital in the economy is not used efficiently, implying productivity losses [51]. From the point of view of the individual worker, the educational mismatch is associated with negative labor market outcomes in the form of lower wages and reduced job satisfaction (e.g., [35]). By looking closer at the situation of university graduates in Spain, one-third of bachelor's degree holders from the class of 2014 were mismatched in their jobs five years after graduation, while 21.5% were in jobs that did not require degree qualifications. Jovanovic's search-and-matching model suggests that mismatched employees change jobs more often at the beginning of their careers until an optimal match is reached [52]. Sub-optimal matches at the individual level are only possible temporarily in this model since increasing experience and on-the-job searches enable a worker to find an optimal match. However, the incidence of educational mismatch in the Spanish graduate labor market has not changed significantly in the last decade, as shown in Table 1. This result suggests that there are structural and job characteristics of the Spanish graduate labor market that may affect the matching process and which the curricular reform has been unable to eliminate. As we anticipated, the vast majority of Spanish firms are small- and medium-sized enterprises (SMEs) and family businesses. An education–occupation match can hardly be achieved even five years after obtaining a university degree. Medium and large companies are those that offer highly qualified jobs and possibilities for promotion through well-defined career ladders; in Spain, they represent less than 5% of businesses.

Imbalances between supply and demand for university degrees are also likely to explain educational mismatches. Spain is an academic secondary education-oriented country. The main consequence of this feature is the "over-production" of university graduates over time that the labor market cannot absorb. In a world of continuous technological change, a dual vocational education and training (VET) system is expected to be less prone to problems of educational mismatch, with firms expected to adapt their training curricula in a timely manner to changes in the skills demanded. Although there have been attempts to reform the formal VET system in Spain, it is still less popular (and receives less social recognition) than the academic upper-secondary curriculum. All of the above arguments may be sufficient to understand why educational mismatch in the graduate labor market is inevitable and structural in Spain. However, is the horizontal mismatch acceptable? After all, graduates are occupying highly qualified positions though, in principle, they do not use the specialized knowledge gained in college. A majority of British graduates, for example, are also employed in small and medium-sized enterprises [3]. However, the UK is probably at the forefront of non-subject-specific recruitment (at least 50% of graduate recruitment is not subject-specific) [3].

In Spain, as well as taking a degree-based view of the graduate labor market, today's labor market should examine the cognitive and non-cognitive skills embodied within university-issued credentials to enable us to judge if Spanish universities make a difference in competence development valued by employers. If the employment-relevant skills that firms require from graduates are "general" (e.g., using time efficiently, working productively with others, or having the ability to rapidly acquire new knowledge), which are transferable from firm to firm (with the employee), the educational mismatch among graduates might not be seen as a "bad" thing in the labor market. Educational (mis)match may not necessarily be equivalent to skill (im)balances.

Finally, we point out some limitations. It is possible that we will face a selection bias problem. However, information on how or why individuals end up in jobs for which they are (mis)matched is rarely available in graduate surveys. The review of Leuven and

Oosterbeek [7] already concluded that the over-education literature has not yet succeeded in addressing the bias resulting from omitted variables, such as unobservable skills and ability, in a satisfying way. It has been argued that over-education might arise as a consequence of skill heterogeneity across graduates with the same degree. Nonetheless, as a novel contribution, this paper identifies, for a sub-sample of workers, the process by which a good match is achieved, that is, how individuals self-select to accept positions in which they can achieve a good match.

6. Conclusions

This article contributes to the literature on educational mismatch by using a novel dataset of 2014 Spanish university graduates who were interviewed five years after graduation. Education–job mismatch occurs when a job requires fewer educational qualifications than those possessed by the worker and/or the field of study is unrelated to the job. This article identified different types of mismatches in the Spanish labor market for recent university graduates by using subjective employee responses to certain survey questions. Regarding the vertical mismatch, the proportion of Spanish university graduates in non-graduate jobs is important five years after obtaining a bachelor's degree. Specifically, 21.5% of graduates are over-qualified. Another possibility in this vertical mismatch scenario is that the work's contents are or are not connected to the field of study. In the former (over-education only), about 7% of Spanish university graduates are over-educated. However, 15% of the over-qualified graduates also hold jobs unrelated to their fields of study (i.e., fully mismatched). Nevertheless, although substantial literature has examined the phenomenon of vertical mismatch, less is known about horizontal mismatch among university graduates. This article shows that about 11% of graduates are in occupations that are not closely related to their fields of study.

By estimating a multinomial logistic regression, this article also identifies bachelor's degree programs that are associated with increased likelihoods of a particular educational mismatch status. Results indicate that an adequate match between qualifications and occupations was more likely among graduates of majors that provide specific human capital. This was the case for university graduates from highly specialized programs, such as health science (e.g., Medicine, Nursing, Veterinary) and STEM degrees. Other degrees, which involve general human capital that has value across various occupations, increased the probability of being horizontally mismatched (e.g., geography and history, sociology, philosophy). For the self-assessed vertical mismatch (over-educated in a related field), some narrow fields of study increased the probability of being vertically mismatched in the current job (e.g., economics, marketing, law, sports science). However, some arts and humanities degree holders were more likely to hold non-graduate positions unrelated to their studies (e.g., language and literature). Regarding other variables, gender appears to have played no role in the matching process; however, mature graduates found it harder to obtain employment with a degree requirement related to their fields. Finally, the probability of an education–job match increased if the degree was earned at a private university and combined with possession of a master's degree.

As a novelty, this paper also identifies, for a sub-sample of workers, the process through which a good match is achieved, that is, how individuals self-select to accept jobs in which they achieve a good match.

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