# The Importance of a First Job Mismatch on the Current Job: Evidence from Spain

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# Contents

**Abstract**

This paper provides an exhaustive analysis of how first job mismatches and current jobs matching status are related in the short run. Special attention is paid to variables like the field of studies or the working schedule as to explain how important initial jobs might be. Using data from the 2014 Spanish Survey on the Labour Insertion of University Graduates (EILU) two different matching definitions were created, characterised by the usage of objective and subjective approaches respectively. Following the two criteria, proper matches were considered taking into account both the level and the branch of study, not just the level as it is more common in the literature. Evidence is found in favour of first job's matching status being a significant factor to explain current job's matching status. By applying the Oaxaca decomposition, we conclude that the total effect is mainly driven by the pure effect.

# 1. Introduction

The share of Spanish population with tertiary education aged between twenty-five and thirty-four years old has drastically increased from 9.8% in 1981 to 41% in 2016. This share stabilised around 40% in 2005 while the average of OECD countries continued to grow rapidly.[1] Comparing the latest available data of 2016, the Spanish share happens to be slightly lower than the OECD average. Deciding to enrol in a university program at the expense of postponing the labour market entry is an important decision to make. People engage in college education pursuing a wide variety of objectives, such as higher reservation wages, better general lifestyles, the higher social prestige university studies grant and the versatility provided by university education. In the Spanish case, parental influence plays an essential role. In many cases, parents push their children towards university believing it is a way to reduce their offspring's future labour uncertainty. A vast amount of resources is every year dedicated to education. In fact, even in times of hardship, public expenditure on university education ac-

[1] OECD database:
https://data.oecd.org/eduatt/population-with-tertiary-education.htm

counted for 20.7% of the total Spanish education budget in 2015.[2] Therefore, the acceptance of jobs for which lower educational attainment is required could be understood as a waste of resources.

The existing tradeoff between prolonging one's studies and postponing the labour market entry usually takes into account aftermath expectations, which could easily change depending on the first job. In this context, individuals tend to set new experiences as anchors, which implies that all similar experiences that take place later on will be in terms of the initial one. Therefore, the first job seems to be of great importance. Besides, this first job may help reform expectations, which will directly affect later possible outcomes. This is even more relevant in the short run, as the memory of that first experience is still vivid.

In order to analyse the importance of the first job on the current one in a framework of financial crisis, we use two different matching definitions; one based on self-reported data and the other measured following more objective approaches. In both cases, we find evidence in favour of an initial match being a relevant factor to explain a posterior outcome. We also decompose the total effect into pure and characteristic effects, concluding that the total effect is mainly driven by the pure effect.

The paper is structured as follows: Section 2 reviews the existing literature and poses the main hypothesis. Section 3 focuses on describing the data and defining the corresponding dependent variables. Section 4 provides some basic and more detailed information about the sample used to carry out this analysis. Section 5 presents the obtained empirical results. The paper concludes with Section 6, where the main conclusions can be found.

[2]Spanish Ministry of Education, Culture and Sport:
https://www.mecd.gob.es/servicios-al-ciudadano-mecd/dms/mecd/servicios-al-ciudadano-mecd/estadisticas/educacion/indicadores-publicaciones-sintesis/datos-cifras/Datosycifras1718ing.pdf

## 2. Literature Review

The literature of occupational path dependence is far from being conclusive. Following various methodological approaches and matching definitions, researchers have often reached different conclusions. While some authors like Alba (1993) and Robst (1995) argue that an inappropriate matching at the first stages of the working career may be a mere stepping stone, others, such as Meroni and Vera-Toscano (2017) or Baert et al. (2013) perceive it as a trap. In this context, the initial over-qualification behaves as a signalling, so that the upcoming matching status will be influenced by the once-in-time mismatch. Even though there is no consensus on the effects of initial mismatches, the most recent literature goes against some versions of the career mobility theory proposed by Sicherman and Galor (1990). This theory suggests that skills and experience accumulated in one job can be transferred to other posterior occupations. Therefore, inappropriate matches at the early stages of the working career may be part of the optimal career path.

Meroni and Vera-Toscano (2017) use the kernel matching procedure and find out that over-education at the beginning of the career leads to greater likelihood of being over-educated later on. They do not find any real differences between apparent and genuine over-education. While the former only takes into account over-education,[3] the latter also includes skill mismatches. Nevertheless, they find some differences across countries. Similarly, Baert et al. (2013) use a mixed proportional hazard model as to investigate whether over-education at the beginning of the career speeds up the transition to adequate employment. They conclude that accepting a job for which one is over-educated substantially retards the transition to an adequate job. They argue that the entrapment effect is likely to be explained by a combination of factors such as negative signalling, reduced job search intensity, job-specific human capital investments, cognitive decline and habituation. Acosta-Ballesteros et al. (2017) use a recursive bivariate

[3]Over-education is defined as having a level of education higher than the one needed to appropriately do a certain job.

probit in order to jointly estimate the effect of the first job's matching status on the current job's status. They employ an objective definition of mismatch based on measuring the required education level to perform their job duties and comparing it with their actual education level. By applying the Oaxaca (1973) decomposition principle, the authors are able to isolate the pure and characteristic effects from the total effect. They conclude that over-education is a trap, where the total effect is mainly driven by the pure effect.

Most of the research done up to now has not distinguished between over-education and over-skilling. One does not always imply the other, although both terms have in many cases been used as interchangeable terms. Nevertheless, authors like Mavromaras et al. (2013) suggest that over-education and over-skilling are indeed different phenomena. Analysing these differences by sex, they find that males only face a significant pay penalty when over-skilling and over-education take place. Females, however, find themselves affected by such penalty in all mismatch cases. Field and educational attainment are also some factors to be considered when job mismatches are analysed. Mavromaras and McGuinness (2012) found that among other factors, over-skilling also differs by educational pathway. While undergraduate and graduate degree holders are less likely to be over-skilled, the over-skilled state dependence happens to be at its worst for higher degree holders. Unlike persistence, which only considers the duration of a given mismatch, state dependence emphasises the importance of occupational paths as factors to explain subjects' current matching status. The degree of state dependence is lower but still present for those with no post-compulsory education and not present for vocational training graduates.

After briefly reviewing some of the existing literature, two main research questions are proposed. On the one hand, we will try to add some evidence about the importance of starting with mismatched initial jobs in the working career. On the other hand, we would also like to see whether labour mismatches affect everyone in the same manner, independently of the field or duration of the degree.

## 3. Data and Variables

### 3.1 Original Data

In this paper, we analyse young people's transition to work. In order to carry out this analysis, we use data from the 2014 Spanish Survey on the Labour Insertion of University Graduates (EILU). This survey aims at collecting data to properly analyse the transition from university to the labour market. For the sake of comparability, EILU is harmonised with the International Survey of Higher Education Graduates (REFLEX). The latter project is a large-scale European survey among higher education graduates, which involves partners from fifteen countries. EILU uses a one-stage random sampling without replacement and with same probabilities in order to provide information of 30,379 individuals who got their undergraduate university degrees during the 2009/2010 academic year. The corresponding data of these subjects were at first taken from databases of different public institutions. Then, apart from that basic information, other self-reported data were collected through an online questionnaire (CAWI) and telephone interviews (CATI) whenever the former method was invalid.

### 3.2 Final Sample

We restrict the original sample size composed only by university students to those under the age of thirty at the time of the interview.[4] Srivastava et al. (2003) found evidence supporting the existence of age effects on one of the Big Five personality traits for both men and women. More precisely, they found out that the changes in conscientiousness are more significant between the ages of twenty-one and thirty. Moreover, high in conscientiousness subjects are also associated with higher levels of anchoring bias (Eroglu & Croxton, 2010). That is, setting an even as an anchor and evaluating future similar events in terms of the anchor. We further

[4]According to EILU, the group of university students is composed by those holding any of the following degrees: *"diplomatura"*, *"grado universitario"* or *"licenciatura"*.

restrict our sample to subjects with no prior working experience who finished studying and did not continue in their first job at the time of the interview. Due to the impossibility to distinguish between good and bad matches, self-employed people were also excluded from the analysis. Following this criterion, armed forces and family jobs were not included either since family ties could very much influence the existence of proper or improper matches. Finally, as a consequence of the information lack regarding subjects' other studies, we decided to exclude those with more than one university degrees. After going through the just mentioned sample selection, we are left with 3,224 individuals. Based on the available information, we create other variables as to capture interesting information, such as different transitions. We are particularly interested in the possible effect of a first job mismatch on the current matching status. The time horizon covered between these two jobs is at most five years. Consequently, we do not expect any problems with qualification requirements changing over time.

### 3.3 Matching Definitions

We analyse the adequacy of different matches using objective and subjective matching definitions. As previously stated, most of the studies only focus on over-education. In this paper, however, independently of the matching definition, we consider as proper matches those cases where both the level and the field of studies are present.

Apropos of the objective definition, we mainly follow the steps set by the International Standard Classification of Occupations of 2008, which evaluates the education level needed to gain the skills that different jobs require based on the International Standard Classification of Education of 1997. Except for a few cases, we only consider as good matches those jobs that require an education level equal to the first stage of tertiary education (5a) or the second stage of tertiary education (6).[5] Then, in order to capture the accuracy of the field, we individually analyse the nature of each occupation the survey provides us with, aggregated at two-digit level, and compare it with the field of achieved studies. That is, we check whether the roles

[5]The numbers reported in parenthesis correspond to the ISCED-97 groups.

and responsibilities carried out in each occupation correspond to the acquired skills through the obtained studies. Following the just mentioned criteria, Table 1 shows that while 53.78% of the subjects were correctly matched in their fist job, 59.51% of them were properly matched in their current job.

In the subjective definition's case, we restrict ourselves to the self-reported data provided by respondents. A good matching is only considered if the next two conditions are met. First, the required education level to carry out the job in a proper manner must be of university type. Second, the area of activity has to be at least related to the one of the university degree attained by the worker. Following the just mentioned criteria, Table 1 shows that while 60.28% of the subjects were correctly matched in their fist job, 69.69% of them were properly matched in their current job.

Note that independently of the matching definition, we observe that as time goes by, the share of matched individuals increases.

## 4. Descriptive Analysis

This section reports the main demographics of the sample from different perspectives. Individuals will be the unit of analysis throughout the whole paper. First, the general demographics will be explained. Next, interactions between matchings and a set of variables composed by the contract type, degree field and work schedule will be analysed. The structure of the survey permits having information about the first job after finishing the university degree and the current job, so that individuals can be tracked at two different moments in time.

Table 2 presents the transition matrixes of the matching status. We observe that for both matching definitions, the most numerous cases are the ones where both status coincide. This suggests that the first job's matching status may be of great relevance in order to explain that of the current job.

We first describe the variables used to explain both first and current job matching status of our sample in Tables 3-5. This collection of tables shows the proportion of matched and mismatched subjects according to some explanatory variables. The number in the left-hand side of each cell corresponds to the objective matching definition, while the right-hand side corresponds to the subjective one. Note that all descriptive evidence involving degree fields, contract type and work schedules will be explained in their own subsections. We perceive that after going through the previous sample selection, the presence of female graduates dominates the one of males. Following the objective approach, females are better matched than males. Such insight does not hold when the subjective approach is considered. Some males' need to maintain a certain superior status may be a good answer to this phenomenon.

In respect of the university type, we perceive that the vast majority of individuals studied in public universities. At the same time, we do not observe big differences between public and private universities in terms of finding a matched first job. Having higher frequencies of matched subjects in the current job for both university types may be attributed to work experience. Degrees' duration does also look like a factor to be taken into account. Although the mode corresponds to degrees consisting on three years of university studies, the longer path provides on average a higher share of good first and current job matches. In respect of having studied abroad and holding a master's degree, our results do not point in the same direction independently of the matching definition. Nowadays, computer skills are an important factor to be considered in almost any type of job. Information and communication technology (ICT) skills are divided in three categories -high, medium, low- and the mode corresponds to having medium skills. As reported by the objective definition, higher ICT skills are associated with better matches. Other type of skills, such as the English level, are also essential for a good match in a globalised world. This language skill is split into four classes -vey good, average, poor, no English- such that the first two are the most common ones. Due to the lack of representability of the other classes, we cannot observe any clear path.

Leaving mainly educational characteristics behind, we now focus on other attributes that could be key determinants to explain the success of a given match. There are many different reasons why people end up getting a job abroad. In any case, the share of subjects with first and current jobs abroad only corresponds to 8% and 10% of our sample respectively.

We see that working abroad does not necessarily imply having better matches on average. The nationality may also influence the matching. Undeniably, we see that those with other nationalities than Spanish face much lower success rates, even after graduating from a Spanish university. The number of methods used to search for a job may also indicate the degree of involvement or the need to use different job search methods. Apparently, those requiring at least three different search methods have on average worse matching prospects than their counterparts with one or two methods. At the same time, the 67% of our sample only used one search method to find their jobs.

One of the main reasons why people engage in internship programmes is because of the more practical and realistic view they provide face to finding a job in the future. We distinguish between curricular and extracurricular internships. While the former is organised or supervised by the university itself, the latter is not. In general terms, extracurricular programmes seem to be slightly more popular among university students, such that 36% of our sample engaged in them compared to 28% of the sample who engaged in a curricular programme. In any case, those who do not engage in any internship have on average better matching results in both cases.

Next we describe in Tables 6-7 those specific variables used to explained only the first job matching status or the current job matching status. Regarding the characteristics to explain the first job, there is a negative relationship between finding proper initial matches and seeking for a job before getting the university degree. At the same time, we think of the time until the first significant job as a variable that could explain the existence of better or worse matches. It took at most one year to 74% our subjects to find their first job. According to our results, postponing the labour market entry for any reason is negatively correlated with finding proper first matches. The methods used to search the first job also give some valuable information that could help explain the posterior matching status. A priori, we do not observe big differences between subjects who use their own initiative to search for a first job and those who do not. Nevertheless, whenever the search method changes and employers take the initiative to approach employees, those being contacted happen to be better matched on average than their counterparts. This makes sense as subjects would have already gone through a pre-selection process.

We now focus on the variables included as control variables only in the current job match equation of the econometric model, which are presented in Table 7. The size of the firm might also be a relevant factor. We use the number of coworkers as a proxy for the size of the firm. There is a clear tendency that relates bigger firms with a higher share of matched subjects. The number of employers the worker has had along the working career is also a factor to be considered as it captures to some extent the duration of held jobs. Note that different jobs may have the same employer. There is a noticeable proclivity for better matches among subjects with less employers. Having many different employers in a short period of time could be understood in some cases as a signal indicating the lack of implication or the ability to fit in a given context. In any labour-related research, subjects' work experience is always an important variable. In our sample, 71% of our subjects happen to have more than two years of work experience, which gives the highest share of correctly matched individuals. Finally, being in the middle of a job search process is also a relevant variable that could explain the matching outcome. As expected, those either searching for a new job or waiting for a given answer have on average a lower portion of matched subjects.

### 4.1 Matching and Contract Type

As previously stated, we aim at analysing whether the first job matching successfulness is a relevant variable to explain the current job in the short run. In order to do so, we think of the contract type and its transitions across jobs as an important factor to be examined. Three different contract types -internship, permanent, temporary- are considered. We clearly observe in Table 4 that as time goes by the share of internship and temporary jobs decrease at the expense of permanent jobs. It is also the case that the highest proportion of proper matches corresponds to internships. According to the objective matching definition, finding a permanent good match happens to be the most complicated scenario, but work experience seems to increase the share of proper matches.

The results of the mentioned transitions are presented in Table 8. We perceive that starting with a permanent contract type gives proportionately the best results if we consider permanent status to be the most desirable one. In the case of temporary and permanent first jobs, the most common categories correspond to those where the former status is maintained. Starting the job career with an internship in order to end up having a permanent contract type provides proportionately better results than starting with a temporary status.

### 4.2 Matching and Study Field

This subsection first describes the existing interactions between matching transitions and university degree fields. Five different fields -arts and humanities, pure sciences, social sciences, architecture and engineering, health sciences- have been considered. We then look at the same interactions by biological sex. Clearly, as reported in Table 3, social sciences are the most common field of studies. It appears that some fields provide better initial and current matches. Studying health sciences, for instance, seems to be the field which assures best posterior matches, whereas the opposite happens with social sciences.

We observe in Table 9 for both matching definitions that in most cases, the transitions from a matching status to the same outcome are the most predominant categories independently of the degree field. Nevertheless, engineering and health sciences seem to be better choices in order to transition from a match to another match, having the latter a higher success rate. This bimodal distribution suggests that independently of the field, first jobs matter in order to explain current jobs. If one wishes to analyse the same transitions by sex, a good starting point would be to first examine the presence of males and females in each field. This field composition is presented in Table 10, where the data suggest architecture and engineering to be a male-only field. Once the interactions by matching transition are carried out for males and females, we see in Tables 11-12 that similar results hold. The main difference between sexes is attributed to engineering and health sciences. While compared to males a lower proportion of females choose to study engineering, those who do so have a much higher success rate when the objective definition is considered. As for heath sciences, high success rates can be found in both cases, but proportionately, the presence of women is higher.

### 4.3 Matching and Work Schedule

The work schedule is also a variable that may determine the matching transition from first jobs to current jobs. This subsection inspects the job matching transitions, taking into account the work schedule, in Table 13 and then interacts each possible transition with their matching counterparts as it is done in Table 14. We consider full-time and part-time jobs, where the presence of the former strictly dominates the latter according to Table 4.

There seems to exist a tendency to end up having a full-time work schedule in the current job, although a favourable starting point appears to ease the transition process quite a lot. Going into more detail, the same bimodal distribution we observed in the case of the degree field is appreciated. Once again, a successful initial match is mainly associated with a posterior proper match and an initial mismatch is also related to a latter mismatch. This correlation holds independently of the matching definition. Due to its representativity, we will principally consider the case where subjects transition from a full-time job to another with this same characteristic. This specific type of transition suggests that a good matching transition is also the one that corresponds to a full-time to full-time work schedule transition.

## 5. Empirical Analysis

### 5.1 Model Specification

In this paper we mainly aim at analysing the effect of the initial job's matching status on the current job's matching status. A priori, based on the evidence provided by the descriptive analysis, we think of the recursive bivariate probit model (RBVP) as the most appropriate tool. Following the steps proposed by Monfardini and Radice (2006), we proceed to use the Wald test and end up rejecting the null hypothesis of exogeneity. In order to get consistent estimates, Heckman (1978) considered that having a full rank regressor matrix is a sufficient condition for the identification of the model parameters in simultaneous equations models with endogenous dummy variables. According to Wilde (2000), the identification of the RBVP model does not require any exclusion restrictions for the exogenous variables if there is sufficient variation in the data. This is ensured by including at least one varying exogenous regressor in each equation. Besides, Li et al. (2017) suggest that the RBVP is a readily implementable and robust empirical tool for estimating the effect of an endogenous binary regressor on a binary outcome variable. Even though normality is not always satisfied using the score test proposed by Murphy (2007), estimating each equation separately, given normal disturbances, provides very similar results. Before the obtained evidence provided by the Wald test, we jointly estimate first and current job equations in the subsequent manner:

$$\begin{aligned} J_c^* &= X'\beta_1 + Z_1'\gamma_1 + J_f'\alpha + \varepsilon_1, \qquad & J_c &= \mathbb{1}(J_c^* > 0) \\ J_f^* &= X'\beta_2 + Z_2'\gamma_2 + \varepsilon_2, \qquad & J_f &= \mathbb{1}(J_f^* > 0) \end{aligned} \tag{1}$$

where $\mathbb{1}(\cdot)$ is the indicator function; $X$ accounts for the common covariates; and for $j = 1, 2$ we denote as $Z_j$ the equation-specific regressors. We assume that the error terms $(\varepsilon_1, \varepsilon_2)$ are drawn from a standard bivariate normal distribution with zero means, unit variances and a correlation coefficient equal to $\rho$. The $\alpha$ in the current job's equation captures the effect of a proper matching in the first job on the current job's matching status, for which a positive sign is expected.

### 5.2 BRVP Model Results

In this subsection we present the results of our model. We first look at the correlation coefficient in Table 15, which in compliance with the Wald test, both equations happen to be significantly correlated at 5% significance level. According to the estimates of the model, having an initial match significantly increases the predicted probability of being correctly matched in the current job. Regarding the set of covariates, we select degree field, degree type, contract type and work schedule as the main characteristics to be analysed. We also observe some differences across study fields; while compared to social sciences fields like architecture, engineering and health sciences increase the predicted probability of having a proper match in any job, studying arts and humanities is only helpful to get a good match in the initial job. In respect of pure sciences, they only augment the predicted probability of having a proper first match. In terms of degree type, the evidence does not point in the same direction independently of the matching definition. As for the contract type, being a trainee mainly increases the predicted probability of having a correctly matched first job compared to workers with temporary status. Finally, compared to individuals with full-time, individuals with part-time schedules have a lower predicted probability of finding a proper initial match.

$$\mathbf{E}\,[\,J_c\,|\,J_f = 1, x_c, x_f\,] = BVN\,[\,x_c'\beta_c, x_f'\beta_f, \rho\,]\,/\,\Phi(\,x_f'\beta_f\,) \tag{2}$$

$$\mathbf{E}\,[\,J_c\,|\,J_f = 0, x_c, x_f\,] = BVN\,[\,x_c'\beta_c, -x_f'\beta_f, -\rho\,]\,/\,\Phi(\,-x_f'\beta_f\,) \tag{3}$$

Note that given the initial job's matching status is measured by a dummy variable, its marginal effect is measured by the difference in conditional probabilities of expressions (2) and (3). In this context, $BVN$ represents the bivariate normal distribution function; $\Phi(\cdot)$ denotes the univariate normal distribution function; $x_c$ captures the regressors of the current job equation; and $x_f$ aggregates the first job equation's covariates.

Using marginal effects, Table 16 captures the obtained results for one of the research questions proposed in this paper. We discover that switching from a mismatch to a match in the initial job significantly increases the predicted probability of being accurately matched in the current job by 29.5% following the objective approach and 15.7% using the subjective one. As for the covariates we have been analysing in more detail, Tables 17-18 capture the effect of discrete changes in four different sample characteristics on the joint predicted probabilities in the following two cases: on the one hand, we pay attention to the case of being matched in the current job and mismatched in the initial job (p10); on the other hand, we also factor in the special case of being correctly matched in both jobs (p11).[6] We observe that varying the study field from social sciences to arts or health sciences significantly decreases the predicted probability of being matched in the current job and mismatched in the

[6]The rest of the tables are available upon the author's request.

initial one. At the same time, switching from social sciences to engineering or health sciences significantly increases the predicted probability of being correctly matched in both jobs. Note that the only change significantly different from the rest is the one of health sciences. Also, no conclusive evidence is found when the degree type is considered. With respect to the first job's contract type, the change from having an internship to a temporary one is significantly different from gaining a permanent status, which does not happen to be significant in both scenarios. In respect of the first job's work schedule, shifting from having a full-time to part-time job significantly increases the predicted probability of being mismatched in the first job and properly matched in the current. Nevertheless, it significantly reduces the predicted probability of being adequately matched in both jobs.

### 5.3 Oaxaca Decomposition

In order to further analyse the first job's importance on the current job matching status, we decompose the total effect into the pure and characteristic effects as proposed by Acosta-Ballesteros et al. (2017).

$$\begin{gathered}\left(\sum_{\forall i \in M} \frac{\mathrm{Prob}\left(J_{ci}=1 \mid J_{fi}=1, x_i, z_{ij}\right)}{N^{m}} - \sum_{\forall i \in NM} \frac{\mathrm{Prob}\left(J_{ci}=1 \mid J_{fi}=0, x_i, z_{ij}\right)}{N^{nm}}\right) \\ = \\ \left(\sum_{\forall i \in M} \frac{\mathrm{Prob}\left(J_{ci}=1 \mid J_{fi}=1, x_i, z_{ij}\right)}{N^{m}} - \sum_{\forall i \in M} \frac{\mathrm{Prob}\left(J_{ci}=1 \mid J_{fi}=0, x_i, z_{ij}\right)}{N^{m}}\right) \\ + \\ \left(\sum_{\forall i \in M} \frac{\mathrm{Prob}\left(J_{ci}=1 \mid J_{fi}=0, x_i, z_{ij}\right)}{N^{m}} - \sum_{\forall i \in NM} \frac{\mathrm{Prob}\left(J_{ci}=1 \mid J_{fi}=0, x_i, z_{ij}\right)}{N^{nm}}\right)\end{gathered} \tag{4}$$

for $j = 1, 2$

The left-hand side of equation (4) shows the total effect of a good match in the first job on the probability of being properly matched in the current job. This total effect is equal to the difference in average conditional probabilities between those matched in the current job conditional to being matched in the first job and those matched in the current job conditional to being mismatched in the first job. The pure effect, represented by the first term in the right-hand side of equation (4) captures the effect of changing the first job's matching status for subjects with the same average characteristics. Meanwhile, the second term constitutes the characteristic effect, which accounts for the difference in average characteristics of matched and mismatched subjects. All initially matched subjects belong to the set $M$, while those not matched belong to the set $NM$.

The results of this decomposition, which are presented in Table 19, indicate that within the framework of an economic crisis, young workers matched in their first job are 58% and 39.6% more likely to be matched in their current job. Note that the quality of initial jobs is more important to explain a favourable current matching status in accordance with the objective definition. Once the total effects is decomposed, we perceive that the total effect is mainly driven by the pure effect, whereas the characteristic effect does not seem to be so relevant. In any case, having a negative characteristic effect indicates that the attributes of first-job-mismatched individuals give a higher probability of being matched in the current job.

## 6. Conclusions

This paper has analysed the importance of getting a good match in the initial job on having a proper match in the current job for Spanish university graduates. It must be noted that our results only consider a time-lapse of five years at most and the time-period coincides with the 2007 financial crisis. Encouraged by the descriptive analysis, we ended up using a BRVP model in order to estimate our objective. After finding evidence supporting our claim, we proceeded to disentangle the pure and characteristic effects from the total effect. As a sensitivity analysis, all results are provided using an objective and a subjective matching definition.

After finding evidence in favour of simultaneous equations models using the Wald test, we moved to test our hypothesis. Our results indicate that having a proper match in the first job significantly increases the predicted probability of being correctly matched in the current job. Nevertheless, huge differences can be found depending on the degree field. Health Sciences and Engineering, for instance, give much higher probabilities of being correctly matched in both jobs than Social Sciences. In respect of the degree duration, no conclusive evidence is found. The contract type and work schedule appear to be relevant variables to explain the existence of matches and mismatches. The Oaxaca decomposition suggests that suitably matched subjects are actually 58% and 39.6% more likely to be matched in their current job according to the objective and subjective definitions respectively. Similarly to what Acosta-Ballesteros et al. (2017) found, the pure effect is the one that mainly drives the total effect. In conclusion, our results go against some versions of the career mobility hypothesis.

The obtained results leave some room for policy recommendation. First, more resources should be dedicated to helping university graduates find their first job after finishing their studies if the investment in public tertiary education is going to be productive. The obtained results could be improved using other different matching definitions and comparing the results since this type of research highly depends on the matching definitions. We could also separate the causes of mismatch, either the level or the field. Finally, improvements could also be done as to capture what specific characteristics of first-job-mismatched individuals give a higher probability of being matched in the current job.

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# Appendix: Tables and Figures

**Table 1: Matching Status by Definition**

| | First Job | Current Job |
|---|---|---|
| **Objective Matching** | | |
| Matched | 53.78% | 59.51% |
| Not Matched | 46.22% | 40.49% |
| **Subjective Matching** | | |
| Matched | 60.28% | 69.69% |
| Not Matched | 39.72% | 30.31% |

Note: Sample size equal to 3,224 subjects. Each definition's percentages add up to 100%.

**Table 2: Transition Matrix by Matching Definition**

| **FJ / CJ** | Matched | Not Matched |
|---|---|---|
| **Objective Matching** | | |
| Matched | 46.41% | 7.36% |
| Not Matched | 13.11% | 33.12% |
| **Subjective Matching** | | |
| Matched | 51.46% | 8.82% |
| Not Matched | 18.23% | 21.49% |

Note: Sample size equal to 3,224 subjects. Each definition's percentages add up to 100%.

Table 3: Sample Description I (%)

| Variables | Total FJ | Matched in the FJ | | Total CJ | Matched in the CJ | |
|---|---|---|---|---|---|---|
| | | Yes | No | | Yes | No |
| **Sex** | | | | | | |
| Female | 68 | 56 / 60 | 44 / 40 | 68 | 61 / 68 | 39 / 32 |
| Male | 32 | 50 / 61 | 50 / 39 | 32 | 57 / 73 | 43 / 27 |
| **University Type** | | | | | | |
| Private | 14 | 53 / 59 | 47 / 41 | 14 | 63 / 74 | 37 / 26 |
| Public | 86 | 53 / 59 | 47 / 41 | 86 | 63 / 69 | 37 / 31 |
| **Degree Field** | | | | | | |
| Arts | 9 | 52 / 54 | 48 / 46 | 9 | 52 / 56 | 48 / 44 |
| Pure Sciences | 7 | 50 / 57 | 49 / 43 | 7 | 54 / 68 | 46 / 32 |
| Social Sciences | 47 | 41 / 47 | 59 / 53 | 47 | 49 / 60 | 51 / 40 |
| Engineerings | 17 | 51 / 65 | 49 / 35 | 17 | 61 / 77 | 39 / 23 |
| Health Sciences | 20 | 88 / 92 | 12 / 8 | 20 | 88 / 93 | 12 / 7 |
| **Degree Type** | | | | | | |
| 5-year degree | 44 | 59 / 59 | 41 / 41 | 44 | 65 / 69 | 35 / 31 |
| 3-year degree | 56 | 50 / 60 | 61 / 40 | 56 | 55 / 69 | 45 / 31 |
| **Studied Abroad** | | | | | | |
| Yes | 20 | 54 / 63 | 46 / 37 | 20 | 57 / 71 | 43 / 29 |
| No | 80 | 54 / 60 | 46 / 40 | 80 | 60 / 69 | 40 / 31 |
| **Master's Degree** | | | | | | |
| Yes | 45 | 52 / 61 | 48 / 39 | 45 | 59 / 70 | 41 / 30 |
| No | 55 | 55 / 60 | 45 / 40 | 55 | 60 / 69 | 40 / 31 |

Note: Sample size equal to 3,224 subjects. Each cell provides the objective and subjective definitions' percentages in the LHS and RHS respectively.

Table 4: Sample Description II (%)

| Variables | Total FJ | Matched in the FJ | | Total CJ | Matched in the CJ | |
|---|---|---|---|---|---|---|
| | | Yes | No | | Yes | No |
| **ICT Skills** | | | | | | |
| High | 19 | 66 / 64 | 34 / 36 | 19 | 69 / 70 | 31 / 30 |
| Medium | 67 | 51 / 58 | 49 / 42 | 67 | 57 / 68 | 43 / 32 |
| Low | 14 | 49 / 67 | 51 / 33 | 14 | 56 / 77 | 44 / 23 |
| **English Level** | | | | | | |
| Very Good | 44 | 54 / 62 | 46 / 38 | 44 | 60 / 72 | 40 / 28 |
| Average | 42 | 54 / 59 | 46 / 41 | 42 | 59 / 68 | 41 / 32 |
| Poor | 5 | 55 / 64 | 45 / 36 | 5 | 57 / 66 | 43 / 34 |
| No English | 9 | 51 / 54 | 49 / 46 | 9 | 57 / 67 | 43 / 33 |
| **Contract Type** | | | | | | |
| Internship | 28 | 60 / 73 | 40 / 27 | 12 | 70 / 79 | 30 / 21 |
| Permanent | 13 | 47 / 57 | 53 / 43 | 45 | 56 / 72 | 44 / 28 |
| Temporary | 59 | 52 / 55 | 48 / 45 | 43 | 61 / 65 | 39 / 35 |
| **Work Schedule** | | | | | | |
| Full-time | 66 | 43 / 32 | 57 / 68 | 75 | 60 / 73 | 40 / 27 |
| Part-time | 34 | 48 / 46 | 52 / 54 | 25 | 59 / 60 | 41 / 40 |
| **Working Abroad** | | | | | | |
| Yes | 8 | 50 / 55 | 50 / 45 | 10 | 62 / 70 | 38 / 30 |
| No | 92 | 54 / 51 | 46 / 31 | 90 | 59 / 70 | 41 / 30 |
| **Nationality** | | | | | | |
| Spanish | 99 | 54 / 60 | 46 / 40 | 99 | 60 / 70 | 40 / 30 |
| Other | 1 | 43 / 29 | 57 / 71 | 1 | 48 / 67 | 52 / 33 |

Note: Sample size equal to 3,224 subjects. Each cell provides the objective and subjective definitions' percentages in the LHS and RHS respectively.

**Table 5: Sample Description III (%)**

| Variables | Total FJ | Matched in the FJ | | Total CJ | Matched in the CJ | |
|---|---|---|---|---|---|---|
| | | Yes | No | | Yes | No |
| **# Search Methods** | | | | | | |
| 1 method | 67 | 54 / 62 | 46 / 38 | 67 | 59 / 70 | 41 / 30 |
| 2 methods | 19 | 58 / 58 | 42 / 42 | 19 | 64 / 74 | 36 / 26 |
| $\geq$ 3 methods | 14 | 49 / 55 | 51 / 45 | 14 | 55 / 65 | 45 / 35 |
| **Internship** | | | | | | |
| **Curricular** | | | | | | |
| Yes | 28 | 49 / 59 | 51 / 41 | 28 | 56 / 71 | 44 / 29 |
| No | 72 | 56 / 61 | 44 / 39 | 72 | 61 / 69 | 39 / 31 |
| **Extracurricular** | | | | | | |
| Yes | 36 | 50 / 59 | 50 / 41 | 36 | 56 / 69 | 44 / 31 |
| No | 64 | 56 / 61 | 44 / 39 | 64 | 61 / 70 | 39 / 30 |

Note: Sample size equal to 3,224 subjects. Each cell provides the objective and subjective definitions' percentages in the LHS and RHS respectively.

**Table 6: FJ Equation Specific Variables' Sample Description (%)**

| Variables | Total FJ | Matched in the FJ | |
|---|---|---|---|
| | | Yes | No |
| **FJ Seeking** | | | |
| While at Uni | 33 | 50 / 57 | 50 / 43 |
| After Uni | 67 | 55 / 62 | 45 / 38 |
| **Time Until FJ** | | | |
| $\leq$ 3 months | 38 | 59 / 69 | 41 / 31 |
| $\leq$ 1 year | 36 | 53 / 59 | 47 / 41 |
| $\leq$ 2 years | 18 | 47 / 54 | 53 / 46 |
| $>$ 2 years | 8 | 44 / 43 | 56 / 57 |
| **Search Methods** | | | |
| **Own Initiative** | | | |
| Yes | 38 | 54 / 57 | 46 / 43 |
| No | 62 | 53 / 63 | 47 / 37 |
| **Employer's** | | | |
| Yes | 15 | 61 / 62 | 39 / 38 |
| No | 85 | 52 / 60 | 48 / 40 |

Note: Sample size equal to 3,224 subjects. Each cell provides the objective and subjective definitions' percentages in the LHS and RHS respectively.

Table 7: CJ Equation Specific Variables' Sample Description (%)

| Variables | Total CJ | Matched in the CJ | |
|---|---|---|---|
| | | Yes | No |
| **Firm Size** | | | |
| $\leq$ 10 coworkers | 24 | 52 / 59 | 48 / 41 |
| $\leq$ 19 coworkers | 8 | 56 / 64 | 44 / 36 |
| $\leq$ 49 coworkers | 16 | 60 / 71 | 40 / 29 |
| $\geq$ 50 coworkers | 52 | 63 / 75 | 37 / 25 |
| **No. Employers** | | | |
| 1 employer | 10 | 68 / 78 | 32 / 22 |
| 2 employers | 28 | 62 / 73 | 38 / 27 |
| 3 employers | 24 | 57 / 69 | 43 / 31 |
| 4 employers | 17 | 57 / 70 | 43 / 30 |
| $\geq$ 5 employers | 21 | 56 / 62 | 44 / 38 |
| **Work Experience** | | | |
| $\leq$ 1 year | 9 | 56 / 62 | 44 / 38 |
| $\leq$ 2 years | 20 | 51 / 61 | 49 / 39 |
| $>$ 2 years | 71 | 62 / 73 | 38 / 27 |
| **On the Job Search** | | | |
| Yes | 29 | 52 / 58 | 48 / 42 |
| Waiting | 4 | 54 / 56 | 46 / 44 |
| No | 67 | 63 / 76 | 37 / 24 |

Note: Sample size equal to 3,224 subjects. Each cell provides the objective and subjective definitions' percentages in the LHS and RHS respectively.

Table 8: **Transition Matrix by Contract Type**

| **FJ / CJ** | Internship | Temporary | Permanent |
|---|---|---|---|
| Internship | 5.92% | 8.79% | 12.89% |
| Temporary | 4.90% | 31.79% | 22.17% |
| Permanent | 0.65% | 2.62% | 10.27% |

Note: Sample size equal to 3,224 subjects. Percentages add up to 100%.

**Table 9: Matching Transitions by Degree Field**

| | Arts | Pure Sciences | Social Sciences | Engineering | Health Sciences |
|---|---|---|---|---|---|
| **Objective Matching** | | | | | |
| Mismatched-Mismatched | 3.11% | 2.44% | 19.89% | 5.92% | 1.76% |
| Mismatched-Matched | 1.14% | 1.17% | 7.52% | 2.59% | 0.68% |
| Matched-Mismatched | 1.17% | 0.86% | 3.92% | 0.83% | 0.59% |
| Matched-Matched | 3.52% | 2.78% | 15.17% | 8.02% | 16.93% |
| **Subjective Matching** | | | | | |
| Mismatched-Mismatched | 2.65% | 1.63% | 14.00% | 2.71% | 0.49% |
| Mismatched-Matched | 1.48% | 1.45% | 10.76% | 3.36% | 1.17% |
| Matched-Mismatched | 1.33% | 0.71% | 4.69% | 1.26% | 0.83% |
| Matched-Matched | 3.48% | 3.45% | 17.05% | 10.02% | 17.45% |

Note: Sample size equal to 3,224 subjects. Each definition's percentages add up to 100%.

**Table 10: Field Composition by Sex**

| | Arts | Pure Sciences | Social Sciences | Engineerings | Health Sciences |
|---|---|---|---|---|---|
| Female | 10.13% | 7.81% | 49.68% | 8.22% | 24.16% |
| Male | 6.41% | 6.03% | 39.65% | 37.03% | 10.88% |

Note: Sample sizes equal to 2,205 and 1,019 subjects respectively. Each row adds up to 100%.

**Table 11: Female Matching Transitions by Degree Field**

| | Arts | Pure Sciences | Social Sciences | Engineering | Health Sciences |
|---|---|---|---|---|---|
| **Objective Matching** | | | | | |
| Mismatched-Mismatched | 3.21% | 2.66% | 20.91% | 2.30% | 2.21% |
| Mismatched-Matched | 1.22% | 1.26% | 8.49% | 1.22% | 0.72% |
| Matched-Mismatched | 1.49% | 0.90% | 4.38% | 0.41% | 0.72% |
| Matched-Matched | 4.20% | 2.98% | 15.90% | 4.29% | 20.51% |
| **Subjective Matching** | | | | | |
| Mismatched-Mismatched | 3.03% | 1.85% | 15.76% | 1.40% | 0.54% |
| Mismatched-Matched | 1.40% | 1.63% | 11.43% | 1.45% | 1.36% |
| Matched-Mismatched | 1.58% | 0.72% | 5.24% | 0.81% | 0.99% |
| Matched-Matched | 4.11% | 3.61% | 17.25% | 4.56% | 21.27% |

Note: Sample size equal to 2,205 subjects. Each definition's percentages add up to 100%.

Table 12: Male Matching Transitions by Degree Field

| | Arts | Pure Sciences | Social Sciences | Engineering | Health Sciences |
|---|---|---|---|---|---|
| **Objective Matching** | | | | | |
| Mismatched-Mismatched | 2.92% | 1.94% | 17.69% | 13.70% | 0.78% |
| Mismatched-Matched | 0.97% | 0.97% | 5.44% | 5.54% | 0.58% |
| Matched-Mismatched | 0.49% | 0.78% | 2.92% | 1.75% | 0.29% |
| Matched-Matched | 2.04% | 2.33% | 13.61% | 16.03% | 9.23% |
| **Subjective Matching** | | | | | |
| Mismatched-Mismatched | 1.85% | 1.17% | 10.20% | 5.54% | 0.39% |
| Mismatched-Matched | 1.65% | 1.07% | 9.33% | 7.48% | 0.78% |
| Matched-Mismatched | 0.78% | 0.68% | 3.50% | 2.24% | 0.49% |
| Matched-Matched | 2.14% | 3.11% | 16.62% | 21.77% | 9.23% |

Note: Sample size equal to 1,019 subjects. Each definition's percentages add up to 100%.

Table 13: Transition Matrix by Work Schedule

| **FJ / CJ** | Full-time | Part-time |
|---|---|---|
| Full-time | 54.98% | 10.76% |
| Part-time | 19.95% | 14.31% |

Note: Sample size equal to 3,224 subjects. Percentages add up to 100%.

## Table 14: Matching and Work Schedule Transitions

| | Full-time/Full-time | Full-time/Part-time | Part-time/Full-time | Part-time/Part-time |
|---|---|---|---|---|
| **Objective Matching** | | | | |
| Mismatched-Mismatched | 17.73% | 3.48% | 7.09% | 4.81% |
| Mismatched-Matched | 5.80% | 1.23% | 3.76% | 2.31% |
| Matched-Mismatched | 3.52% | 1.05% | 1.82% | 0.99% |
| Matched-Matched | 27.94% | 5.00% | 7.28% | 6.20% |
| **Subjective Matching** | | | | |
| Mismatched-Mismatched | 9.13% | 2.44% | 4.78% | 5.15% |
| Mismatched-Matched | 8.23% | 1.30% | 5.95% | 2.74% |
| Matched-Mismatched | 4.38% | 1.45% | 1.88% | 1.11% |
| Matched-Matched | 33.24% | 5.58% | 7.34% | 5.30% |

Note: Sample size equal to 3,224 subjects. Each definition's percentages add up to 100%.

**Table 15: Recursive Bivariate Probit Regression Results**

| | Objective Definition | | Subjective Definition | |
|---|---|---|---|---|
| **Variables** | FJ | CJ | FJ | CJ |
| First Job | - | 0.811** | - | 0.475** |
| Arts | 0.369*** | −0.042 | 0.187** | −0.267*** |
| Pure Sciences | 0.291*** | 0.063 | 0.162* | 0.015 |
| Engineering | 0.214*** | 0.306*** | 0.229*** | 0.205** |
| Health Sciences | 1.338*** | 0.958*** | 1.429*** | 1.183*** |
| 3-year degree | 0.224*** | 0.127** | −0.060 | −0.068 |
| Internship | 0.351*** | 0.039 | 0.473*** | 0.192** |
| Permanent | −0.018 | −0.194*** | 0.013 | −0.023 |
| Part-time | −0.160*** | 0.037 | −0.422*** | −0.132** |
| $\rho$ | 0.397** | 0.397** | 0.298** | 0.298** |

Note: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Robust standard errors used to compute different variables' significance levels. Reference categories: initial mismatch, social sciences, 5-year degree, temporary and full-time respectively among many others.

**Table 16: First Job Marginal Effect**

| | $\Delta\,\text{Prob}(J_c = 1, \bar{x})$ | |
|---|---|---|
| | Objective | Subjective |
| $\Delta$ FJ Match | 0.295** | 0.157** |

Note: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Delta-method standard errors used. Sample size equal to 3,224 subjects. As for $\bar{x}$, it includes all exogenous variables evaluated at their most common values.

Table 17: **Marginal Effects on First Job Mismatched and Current Job Matched Subjects by Matching Definition (p10)**

| | Objective | | | Subjective | | |
|---|---|---|---|---|---|---|
| | Margins | CI | | Margins | CI | |
| **Degree Field** | | | | | | |
| Δ Arts | $-0.080^{***}$ | $(-0.127$ | $-0.033)$ | $-0.090^{***}$ | $(-0.126$ | $-0.043)$ |
| Δ Pure Sciences | $-0.045^{*}$ | $(-0.098$ | $+0.006)$ | $-0.037$ | $(-0.089$ | $+0.013)$ |
| Δ Engineering | $0.023$ | $(-0.022$ | $+0.069)$ | $-0.024$ | $(-0.069$ | $+0.020)$ |
| Δ Health Sciences | $-0.142^{***}$ | $(-0.185$ | $-0.100)$ | $-0.202^{***}$ | $(-0.247$ | $-0.156)$ |
| **Degree Type** | | | | | | |
| Δ 3-year degree | $-0.018$ | $(-0.050$ | $+0.014)$ | $0.001$ | $(-0.031$ | $+0.354)$ |
| **FJ Contract Type** | | | | | | |
| Δ Internship | $-0.069^{***}$ | $(-0.096$ | $-0.042)$ | $-0.109^{***}$ | $(-0.141$ | $-0.078)$ |
| Δ Permanent | $0.003$ | $(-0.024$ | $+0.031)$ | $-0.003$ | $(-0.039$ | $+0.329)$ |
| **FJ Work Schedule** | | | | | | |
| Δ Part-time | $0.032^{**}$ | $(+0.006$ | $+0.058)$ | $0.110^{***}$ | $(+0.077$ | $+0.143)$ |

Note: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Delta-method standard errors used to calculate the confidence intervals. Sample size equal to 3,224 subjects. Reference categories: social sciences, 5-year degree, temporary and full-time respectively. The rest of the variables are set at their most common values.

**Table 18: Marginal Effects on First Job Matched and Current Job Matched Subjects by Matching Definition (p11)**

| | Objective | | Subjective | |
|---|---|---|---|---|
| | Margins | CI | Margins | CI |
| **Degree Field** | | | | |
| Δ Arts | 0.113*** | (+0.048 + 0.178) | 0.015 | (−0.053 + 0.084) |
| Δ Pure Sciences | −0.100*** | (+0.036 + 0.164) | 0.053 | (−0.013 + 0.119) |
| Δ Engineering | 0.093*** | (+0.036 + 0.151) | 0.097*** | (+0.041 + 0.154) |
| Δ Health Sciences | 0.484*** | (+0.439 + 0.529) | 0.459*** | (+0.411 + 0.507) |
| **Degree Type** | | | | |
| Δ 3-year degree | 0.084*** | (+0.044 + 0.123) | −0.027 | (−0.068 + 0.013) |
| **FJ Contract Type** | | | | |
| Δ Internship | 0.112*** | (+0.070 + 0.154) | 0.140*** | (+0.100 + 0.180) |
| Δ Permanent | −0.005 | (−0.049 + 0.037) | 0.004 | (−0.041 + 0.049) |
| **FJ Work Schedule** | | | | |
| Δ Part-time | −0.050*** | (−0.082 − 0.018) | −0.136*** | (−0.171 − 0.101) |

Note: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Delta-method standard errors used to calculate the confidence intervals. Sample size equal to 3,224 subjects. Reference categories: social sciences, 5-year degree, temporary and full-time respectively. The rest of the variables are set at their most common values.

**Table 19: Oaxaca Decomposition by Matching Definition**

| Total Effect | Pure Effect | Characteristic Effect |
|---|---|---|
| 0.580 / 0.396 | 0.620 / 0.553 | −0.040 / − 0.157 |

Note: Each cell provides the objective and subjective definitions' results in the LHS and RHS respectively.