Job mismatch and postgraduate education: does migration help?

Abstract

Despite the increase in the number of doctoral courses, PhD holders face many obstacles in finding non-academic jobs matching their competencies. Migration may represent not only a way to favour the education-job match at an aggregate level, but also a way of getting a stronger motivation in searching for a suitable job at an individual level. Exploiting Italian Census microdata, this paper looks at the impact of migration, at different "times" and "distances", on the education-job match, measured in terms of *overeducation, overskilling* and *satisfaction*. Besides finding some positive effects of migration, our contribution highlights two relevant gaps. The first between domestic and foreign workers and the second between genders.

Keywords: Education-job mismatch; PhD; Human capital migration; Italian regions.

JEL classification: I21; J24; J61; R23

1. Introduction

Over the last decades, tertiary education and doctoral studies have become increasingly important in Europe. Investment in human capital has been shown to be crucial in promoting research and development (R&D), innovation and, thus, long-term growth (Romer, 1986; Lucas, 1988). However, the effects on growth depend crucially on PhD graduates' opportunity to find jobs matching their educational qualifications, allowing them to exploit their competencies and acquired skills. This education-job match is not easy to achieve (Gaeta, 2015) and, in fact, the mismatch between education and job might explain why, despite the increasing number of doctoral graduates, the share of R&D personnel, in both public administration and private institutions, has not grown much across the European countries. Italy represents the perfect example of this mismatch. Indeed, it has experienced a huge increase in the number of PhD graduates, while, simultaneously, lagging behind in the number of R&D employees (OECD, 2017; ISTAT, 2018). This poses a crucial question on the actual employment opportunities of doctoral students.

Recent studies have already shown that PhD holders face remarkable obstacles in finding a non-academic occupation in line with their competencies (Di Paolo and Mañé, 2016; Gaeta et al., 2017). However, the role of space is often neglected or, at best, underplayed. The education-job match depends crucially on the geographical location where PhD holders live or migrate to. As extensively shown in traditional human capital literature (Sjaastad, 1962), migration is an investment people make with the aim of improving their social and economic status. In fact, voluntary migration of people – especially of the youngest and brightest – is often motivated by the search for better employment opportunities fit for their educational level (Greenwood 1975, 1985; Docquier et al., 2014; Williams et al., 2018). While a number of studies already looked at the impact of spatial mobility on the education-job match of university graduates (Dolton and Silles, 2008; Iammarino and Marinelli, 2015), the literature on PhD holders is still at an embryonic stage (Di Cintio and Grassi, 2017; Alfano et al., 2019a; Ghosh and Grassi, 2020; Alfano et al., 2021). Nonetheless, studying the role of spatial mobility on the education-job match of PhD graduates has important policy implications, especially as doctoral degrees are expanding, and a better knowledge of the role of mobility would allow to devise more effective policies to fully exploit the potential of highly skilled individuals for local economic growth. Indeed, previous studies already show that the matching between jobs and educational level, as well as migration, have a key role in determining regional economic performance in Europe (Rodríguez-Pose and Vilalta-Bufi, 2005).

Therefore, we contribute to the current literature by investigating specifically the role of migration on the education-job match (or mismatch) of PhD graduates. To this end, we consider the role of migration not only on *overeducation* but also on *overskilling* and *satisfaction*. In the first stage, the role of migration is analysed irrespective of where it is directed to and when it happens in an individual's educational path. Subsequently, we extend our analysis in two further ways: first, by considering spatial mobility both within (*short migration*) and between the NUTS1 region of origin (*long migration*); second, disentangling migration flows according to the possible stages of an individual career (i.e., high school to university, university to PhD and, finally, PhD to labour market). In short, we will try to answer the following research questions:

- RQ1: *Does migration "grease the wheels" of the education-job match for PhD holders?*
- RQ2: *How do different investments into migration – measured by "time" and "distance" of migration - affect educational mismatch?*

In formulating this second question, we assume that people that migrate early, and to longer distances, make the highest investment in migration.

Our empirical analysis explores the Italian case, which is very interesting for many reasons. First and foremost, the well-known North-South divide may translate into significantly different job opportunities for doctoral graduates located in different regions, irrespective of the quality of the local higher education institutions. To carry out the analysis, we use data of Italian doctoral graduates at Census level from the most recent "Survey on the employability of PhD holders" ("*Indagine sull'Inserimento Professionale dei Dottori di Ricerca*") by ISTAT (2018). Using self-selection and multivariate Probit models, our results show that migration overall positively influences the education-job match of PhD holders. In particular, migration flows at an early stage of an individual career (from high school to university) significantly reduce the probability of overeducation. However, this holds only if migration is outside the NUTS1 region of origin. We also find that working abroad significantly reduces both overeducation and overskilling, while increases job satisfaction. Finally, we find an alarming gender gap.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature. Section 3 presents the data and the variables. Sections 4 and 5 illustrate the empirical strategy and the results respectively. Section 6 concludes.

2. *Background literature*

The generalized increase in educational levels in recent years has not been followed by a rise of employment in R&D and in knowledge intensive sectors. This suggests that the labour market structure is not able to absorb highly skilled individuals in occupations that fit their competencies and skills. This phenomenon has stimulated scholars to investigate the education-job mismatch and, in particular, the role of migration as an investment to "*reap the rewards to human capital*" (Faggian et al., 2019, p. 151). Indeed, migration has changed over time going from being “forced” to “voluntary” and involving a growing share of highly educated individuals who invest in spatial mobility to improve their social and economic conditions (Faggian et al., 2017).

Traditional human capital migration literature consists of two main streams of research. The first focuses on the motivation to migrate by high-educated individuals. In this respect, several contributions underline the role not only of economic and environmental determinants, for example, the presence of agglomeration economies and the size of the local labor market, (see, among the others, Biagi et al., 2011; Faggian and Franklin, 2014; Baláž et al., 2016; Ortensi et al., 2018; Williams et al., 2018; Berlingieri, 2019), but also that of individual characteristics, such as gender (Williams et al., 2018; Impicciatore and Panichella, 2019) and age (see Otrachshenko and Popova, 2014; Van Mol, 2016), individual personal traits, like students' quality (Faggian and Franklin, 2014), and individuals' openness to change and extroversion (Crown et al., 2020).

The second stream explores the returns of human capital migration in terms of better job opportunities (see, among the other, Devillanova, 2013; Di Cintio and Grassi, 2013; Jewell and Faggian, 2014; Croce and Ghignoni, 2015; Abreu et al., 2015; Iammarino and Marinelli, 2015). Indeed, since migration is an investment people make in their future, it is very likely to influence both the economic rewards individuals get in the destination country and the matching between knowledge, competencies and job tasks (see the seminal work by Sjaastad, 1962). However, few studies also argue that immigrants may experience overeducation since they face higher barriers to entry into the labour market in the unknown destination countries and thus they may divert their skills towards self-employment opportunities (Ulceluse, 2020).

These two streams of literature are strictly connected: individuals with higher personal motivation should also get higher returns from migration. This article aims to investigate also this relationship by assuming that individuals who decide to migrate and, in particular, choose to do that in the initial stage of their educational career and farther from their region of origin may have a stronger motivation to get better job opportunities. To this end, we measure the job opportunities by looking at a wide range of features (i.e., overeducation, overskilling and satisfaction), while most studies limit the analysis to the wage premia derived from migration.

Our expectations are supported by the evidence shown in Jewell and Faggian (2014) on UK university graduates. The authors find that migration at an early stage of educational careers and repeated over time (i.e., from school to university and from university to first job) is associated with higher job opportunities than late migration (i.e., migration for work).

Until recent times, the literature has focused, however, almost exclusively on university graduates. For instance, looking at the case of Italian graduates, Devillanova (2013) finds some evidence in favour of the relationship between migration and education-job match, but only after controlling for a set of job characteristics. Using a similar dataset, Croce and Ghignoni (2015) find that higher educated individuals are more likely to migrate and, at the same time, to get better job opportunities in terms of educational matching. Still, on Italian graduates, Di Cintio and Grassi (2013) explore the impact of migration at different stages of an individual's life cycle on the wage premia. They find that higher returns can be achieved when the decision to migrate is postponed after graduation achievement. Differently, Abreu et al. (2015) find, looking at UK graduates, that migrating to a different location either to university or after graduation has a positive impact on career satisfaction. Finally, Iammarino and Marinelli (2015) explore the relation between the interregional migration of Italian graduates and the phenomenon of overeducation in the labour market. In particular, the authors find significant advantages in terms of education-job matching for those graduates moving from Southern to Northern regions.

Only recently, scholars are focusing attention on doctoral graduates. However, most of the research seems mainly to look at the determinants of educational mismatching in entering the labour market and its impact on earnings or at the impact of the sector of activity on job satisfaction (see, among the others, Gaeta, 2015: Di Paolo and Mañé 2016; Gaeta et al., 2017, Alfano et al., 2021)[1], while the role of migration is still under-investigated. For example, Jewell and Kazakis (2020) provide a deep analysis on the topic by looking at a sample of European doctoral holders, while few attempts exist on the Italian case. To the best of our knowledge, there are only three Italian studies on the relation between migration and education-job mismatching of doctoral graduates (Di Cintio and Grassi, 2017; Alfano et al., 2019a; Ghosh and Grassi, 2020). These studies mainly concentrate on international or interregional migration as an investment people realize in the final stage of their education path, i.e., from PhD studies to the job market. For instance, Alfano et al. (2019a) look at the role of interregional spatial mobility as a way to ease the education-job match. Specifically, using data of two cohorts of Italian PhD holders (2008 and 2010), the authors find that the positive effect on the education-job match occurs only when mobility within Central and Northern regions is considered, despite most of the flows occur from Southern to Central-Northern regions. This is probably a consequence of lower job search costs in moving within Northern regions. From another perspective, Di Cintio and Grassi (2017) and Ghosh and Grassi (2020) focus on the role of international migration on the inbound of PhD holders in the labour market. Di Cintio and Grassi (2017), using data on the population of Italian

[1] For instance, Gaeta (2015) investigates the factors associated with the likelihood of being overeducated and overskilled showing that family background, as well as being self-employed or having a permanent job position, plays a major role. Similar results emerge in Di Paolo and Mañé (2016) that show, in addition, a remarkable wage penalty for those Spanish PhD holders who are both overeducated and overskilled. Slightly different results are in Gaeta et al., (2017). They analyze the wage penalty associated with overeducation, overskilling and dissatisfaction using data on Italian PhD holders and show that overeducation and dissatisfaction are associated with a considerable wage penalty, but not overskilling.

PhD holders in 2004 and 2006, provide evidence of a wage premia induced by international mobility. Similar results are in Ghosh and Grassi (2020), where the role of international migration on overeducation and overskilling is explored using four cohorts of Italian PhD graduates (2004, 2006, 2008, 2010). They find that investments in international spatial mobility are very effective in reducing the likelihood of education-job mismatching.

Building on this framework, we contribute to the existing literature providing novel and update evidence on the role of spatial mobility as a way to reduce education-job mismatch. First, our analyses are based on the last wave of the Italian survey at census level (ISTAT, 2018), i.e. all people who received the doctoral graduation in 2012 and 2014. To the best of our knowledge, no other studies have still explored this dataset. Second, differently from the above-mentioned studies, we analyse in a unique framework both the role of regional and international migration and extend the investigation to migration in different stages of an individual's education path. Finally, we look not only at overeducation and overskilling, as usually done in literature, but also at satisfaction. As suggested by Gaeta et al. (2017), satisfaction allows exploring the phenomenon of overskilling with a different lens than that usually used in the traditional literature.

The next section includes a description of the dataset and the variables employed in the following analysis.

3. *Data and variables*

The dataset used in our analysis comes from ISTAT and it includes the occupational status of PhD holders 4 and 6 years after graduation. The dataset collects information on 22,098 PhD holders (11,459 in 2012 and 10,639 in 2014). The response rate is very high, with approximately 72% of interviewees providing answers to the questionnaire. However, the questions on educational mismatching were only asked to respondents who started their current job after the end of their doctoral studies. Of course, the respondents who started their current job before concluding the doctoral studies (about 27%) are, by default, subject to some degree of educational mismatching. Respondents who did not get a job at the time of the interview are also excluded by the dataset (about 6% of the population). Therefore, we finally explore a dataset including approximately 10,500 PhD holders representing about 50% of the population. This is a very large share of the population that guarantees the reliability of our analysis. Table 1 reports the list of all variables employed in this study, while Tables 2 and 3 some main descriptive statistics.

<*please, insert table 1 about here*>

Table 2 shows that 19% of PhD holders declare to have experienced overeducation, 50% overskilling, while more than 73% is satisfied with the use of their competencies. We note that females are slightly more penalised than males (53% and 47% respectively) and that 43% of respondents are married and 32% have children. Most of the respondents have both parents employed (53%) and 80% have at least one parent with a degree or a higher education level. In addition, 28% of the respondents works in universities, while only 5,49% in R&D departments of private institutions. A large share had teaching experience during their PhD (70.88%), while slightly less than 50% had a visiting abroad. Almost 19% of respondents work abroad (see the '*Labour Market*' variable), while about 22% work in the North-West, 16% in the North-East, 23% in the Centre and 20% in the South.

<*please, insert table 2 about here*>

As for migration flows, Table 2 shows that many had no migration experience (45%), but those who decided to migrate preferred destinations outside their NUTS1 region of origin. Table 3 reports the breakdown of migration flows by stage of education path. Among migrants, 17% decided to migrate in the last stage (PhD to labour market), 6.50% in the first stage (high school to university) and only 2.57% in the second stage (university to PhD). The remaining 28% has experienced a repeated migration.

<*please, insert table 3 about here*>

4. Empirical strategy

Our first research question (*RQ1*) aims to assess the impact of migration in general on the education-job mismatch. In this stage, we do not look at the heterogeneity in the migration phenomenon, but simply at the comparison between migrants and non-migrants. The idea is simply that people who have had at least a migratory experience – independently of time and distance moved - have a benefit in terms of education-job match.

Empirical literature suggests to control for a potential endogeneity of migration in this type of investigation (see, among the others, Alfano et al., 2019a; Devillanova, 2013; Croce and Ghignoni, 2015; Ghosh and Grassi, 2020). In short, the decision to migrate could be associated with unobservable individual characteristics, which in turn may also affect the education-job mismatch. Ghosh and Grassi (2020) assert that "*if migration is positively related to ambition (or ability) then* *migration and mismatching might be negatively correlated even in the absence of a true causal relationship*" (p. 10). To this end, we first estimate a selection equation as follows[2]:

$$\Pr(Migration = 1) = \alpha + \vartheta X + \varphi E + u \qquad (1)$$

Where *Migration* is a dummy assuming value equals to 1 if the individual has migrated at least once in his life and 0 otherwise; X is a matrix of covariates that includes some main individual's characteristics (gender, parents education and parents occupation); the matrix E includes the exclusion restrictions that are the *Age of Graduation* and the NUTS2 region of origin (*Regions*). The first variable is used as proxy of individual's abilities (Labrianidis and Vogiatzis, 2013; Clark et al., 2019), while the second measures the role of space on the decision to migrate. As suggested by past evidence, people who graduate later should be less likely to migrate (Otrachshenko and Popova, 2014; Van Mol, 2016), while those living in peripheral and/or less developed regions, e.g. the South of Italy, should be more likely to migrate (Ballarino et al., 2014; Impicciatore and Panichella, 2019).
The equation (1) allows us to control the equation (2) for potential endogeneity effects of migration on the education-job match as follows:

$$\begin{cases} \Pr(Overeducation = 1) = \beta_1 X + \delta_1 Z + \theta_1 T + \mu_1 R + \gamma_1 Migration + \lambda_1 IMR + \varepsilon_1 \\ \Pr(Overskilling = 1) = \beta_2 X + \delta_2 Z + \theta_2 T + \mu_2 R + \gamma_2 Migration + \lambda_2 IMR + \varepsilon_2 \\ \Pr(Satisfaction = 1) = \beta_3 X + \delta_3 Z + \theta_3 T + \mu_3 R + \gamma_3 Migration + \lambda_3 IMR + \varepsilon_3 \end{cases} \qquad (2)$$

We consider the education-job match as a multidimensional phenomenon that can be measured under the following three perspectives (see Gaeta et al. 2017):

- *Overeducation*, i.e. the PhD is required to get the job;
- *Overskilling*, i.e. the PhD is necessary to do the job;
- *Satisfaction*, i.e. the PhD holder is satisfied of using the knowledge acquired during the doctoral studies for doing the job[3].

The first two variables are binary, while the third is originally measured by a Likert scale 0-10. However, we need to apply the same scale to the three variables if we want to model the phenomenon as multidimensional by means of a Multivariate Probit. To this end, we transform *Satisfaction* into a binary variable as follows: 0-5 unsatisfied; 6-10 satisfied.

[2] Subscripts are omitted for simplicity.
[3] The questionnaire specifically asks PhD the following questions: "Was the doctorate expressly required to access your current job?" (Overeducation); "In your opinion, is the doctorate necessary to carry out your current job?". (Overskilling); "how satisfied are you in the use of the knowledge acquired during the doctorate" (Satisfaction).

Satisfaction is usually employed in literature as a more accurate measure of overskilling (Allen and van der Velden, 2001; Iammarino and Marinelli, 2011; Gaeta, 2017). For example, respondents might use the skills acquired during doctoral studies, so overskilling is not recorded, but this use could be at a lower intensity so that they might declare to be unsatisfied.

As regards the other covariates, *X* refers to "individual-level variables" (e.g., age, gender, marital status, etc.); *Z* includes "job-related variables" (e.g., type of contract, sector of activity, etc.); *T* "education-related variables" (e.g., years of PhD completion, field of study, etc.); *R* includes a set of dummies to compare the "regional labour markets" at NUTS1 level to the international market (reference); the *Migration* is a dummy as above descried; finally *IMR* is the Inverse Mills Ratio from equation 1 to control for a possible endogeneity of migration.

The second research question (*RQ2*) explores the impact of different investment into migration on the educational-job match. As we said above, we consider the investment into migration in terms of "time" and "distance" so that people who decide to migrate at the beginning of their educational path and to more distant destinations make the highest investment and should have the highest return in term of education-job match. In practice, *Migration* is decomposed to measure the "time" of migration (see Jewell and Faggian, 2014): (i) from high school to university[4]; (iii) from university to PhD; (iii) from PhD to job market. And, within each "time", the "distance" of migration, i.e. inside or outside the NUTS1 region of origin.

5. *Empirical Results*

Table 4 reports the results from the estimation of equation 1. We find that females have a lower propensity to migrate than males (see Ortensi et al., 2018). The probability to migrate increases for individuals whose parents have higher educational levels and are employed (Labrianidis and Vogiatzis, 2013). In line with previous studies, we find that the probability of migration is lower for people who get their degree late (Otrachshenko and Popova, 2014; Van Mol, 2016). Finally, individuals from the Southern regions (e.g., Puglia, Basilicata, Campania, Calabria and Sicily) are more likely to migrate. This corroborates the discussion provided in Impicciatore and Panichella (2019) who analyse Italian internal migration from the South to the North. Importantly, these estimates allow us to control for endogeneity of migration in equation 2 by including the Inverse Mill's ratio across the covariate. If this is not significant, we can conclude that the relationship

[4] We excluded in the first migration stage people that came from abroad and enrolled in Italian universities. They amount to a handful of observed units. In the second migration stage, we have only people enrolled in Italian universities to attend a PhD program.

between endogeneity and education-job match variable (overeducation, overskilling, satisfaction) is not affected by endogeneity issues.

Table 5 provides the results from the multivariate Probit model described in equation 2. Many interesting results emerge looking at the set of "individual-level variables". First, we observe that older respondents are more likely to enter the labour market with both overeducation and overskilling, as well as they are less likely to be satisfied with their job. Confirming some past evidence (see Croce and Ghignoni, 2015; Alfano et al., 2019b), we find significant gender discrimination with females facing less favourable job opportunities than males. Unexpectedly, being *Married* and having *Children* do not play a role. However, we cannot be sure that individuals get married and have children before entering the labour market. As in Croce and Ghignoni (2015), we also try to interact with the *Female, Married* and *Children* but no significant effects emerged from interaction terms. Therefore, gender discrimination could exist independently of women's family status. These results are not reported here for brevity, and however they should be interpreted with caution for the reasons above mentioned. As the family of origin concerns, we find only a few significant effects[5]. The probability of getting overeducated jobs is lower if parents are highly educated (*Parents Education*), while satisfaction depends on having both parents employed (*Parents Occupation).*

Looking at the "job-related variables", we find that respondents with fixed-term or atypical contracts are less likely than those with permanent contracts to report overskilling (see Gaeta, 2015). This result points to a potential trade-off between finding a permanent job or finding one "fitting" to their education and skills. As for *Experience*, we observe that more experience does not reduce the education-job mismatch. However, this result could be affected by the economic cycle, as more years of experience (e.g., 4, 5 and 6 years) correspond to periods of intense economic depression (i.e., 2014, 2013, 2012). Interesting results come from the variable *Sector of Activity*. Lower probabilities of educational mismatching, in terms of all three measures here explored, are found in respondents who hold public R&D or academic positions, while alarming results emerge for the private R&D where people are more likely to experience phenomena of education-job mismatching. This last evidence could be interpreted as a signal of potential underutilization of employees' competencies and skills, as also highlighted by Di Paolo and Mañé (2016).

The next set of covariates includes some features of the doctoral studies, i.e. the "education-related variable". We find that respondents who specialized in social sciences (SH) are more likely to suffer from overeducation (see Di Paolo and Mañé, 2016). Moreover, we find a positive influence of *Scholarship* on both overeducation and satisfaction, while *Degree Grade* reduces the probability to have overeducated jobs. Students who decided to spend a period abroad during their PhD (*Visiting*)

[5] Gaeta (2015) obtains similar results by exploring data on some previous cohorts of PhD holders.

are less likely to report overeducation and overskilling and more likely to be satisfied with their job (see Gaeta, 2015). In line with Ghosh and Grassi (2020), we find that having completed the PhD on time is negative and statistically significant but only on overeducation.

Finally, we control our estimates for the "regional labour market" where people get their job. We find worse occupational conditions (higher probabilities of overeducation and overskilling, and lower of satisfaction) in all Italian NUTS1 regions in comparison with the international labour market taken as reference category. The result is in line with that of Ghosh and Grassi (2020) who find a positive impact of international mobility on the educational-job match. In line with the expectations, we find that *Migration* greases the wheels of the education-job match of PhD holders. Indeed, its impact is negative and significant on the probability of both overeducation and overskilling. We do not find evidence of sample selection bias, i.e. the Inverse Mill's ratio (IMR) is never statistically significant. This may be explained by the fact that we use population data and, moreover, that such endogeneity issues do not seem to affect the migration of PhD graduates but only those with lower education levels since highly educated individuals form a very homogeneous group (see, on this point, McGuinnes and Sloane, 2011 and Ghosh and Grassi, 2020). The "Correlation of Error Terms" is instead significant, and this confirm the choice of a multivariate model to investigate the three dimensions under analysis of the education-job match (i.e. overeducation, overskilling and satisfaction).

The results of our second research question are reported in Table 6. Results on "individual level variables", "job-related variables" and "education-related variables" are in line with those discussed in Table 5. Here, we specifically focus on the return from the investment people make migrating in different "time" and "distance". In this respect, we can overall conclude that spatial mobility could be a way to reduce the education-job mismatch as already shown in Table 6[6]. However, not all migrations get the same effect. For example, a lower probability of overeducation is associated with PhD holders who decide to migrate in the first stage of the educational path (from high school to university) and to a more distant destination (outside the NUTS1 region of origin). This result is very interesting if we consider that estimates are also controlled for people that work abroad. In other words, independently on the market where people work, higher is the investment into migration – in terms of both "time" and "distance" – lower is the probability to get overeducated job positions.

We have to note that inter-regional migration effects may be hidden by the sizeable gap between domestic and foreign labour markets. For this reason, in the next section, we will replicate the analysis isolating the sub-population of people who works in the domestic market. In addition to this, other robustness checks will also be provided.

[6]Alfano et al. (2019a) reach to a similar conclusion using older data but limiting the analysis to overeducation and not controlling for people working abroad.

<please, insert tables 4 to 6 about here>

6. Robustness Checks

In this section we provide some robustness checks by excluding some specific categories of respondents that may influence the results described above. First, as suggested by Ghosh and Grassi (2020), individuals who get academic positions should be rarely exposed to phenomena of education-job mismatching. This could be true if we look at overeducation, but it is not so obvious if we look at overskilling and satisfaction. Surely, further investigation needs on this point, as we will do below. A second point to furtherly investigate concerns the difference between domestic and foreign labour markets. Alfano et al., (2019a) suggest excluding people who get a job abroad to better explore the impact of regional flows of migration on the education-job matching.

To focus on the previous points, we compare estimates of our model specification in Table 6 with those obtained by excluding all respondents who get an academic job and who get a job abroad (see Tables A1 and A2 in the Online Appendix).

Empirical results appear to be very stable. Unfortunately, gender discrimination is dramatically robust with respect to all the models estimated. A noteworthy result refers to the typology of job contract. When we exclude people who get an academic job or a job abroad, we find that a fixed-term contract significantly reduces the probability of being satisfied. This means that people may be satisfied with fixed-term contracts when balancing them with other conditions such as working in an academic context or in an international market. Looking at migration, we still find a positive effect on education-job match. This especially when migration occurs early in the individual's educational path and outside the NUTS 1 of origin. Unexpectedly, Table A.2 does not reveal a North-South divide. Taking as reference the North-West, we do not find any significant differences across the NUTS1 regions. The only exception refers to the probability of overeducation that results higher in the case of the North-East.

7. Conclusion

Despite the increasing importance of doctoral education, PhD graduates find remarkable obstacles in finding suitable job positions, especially outside the academic world. Italy is a perfect example of this kind of education-job mismatch as the number of R&D employees remains, both in public and private institutions, far away from the average European level. This mismatch may be a strong determinant of the decreasing productivity level of the country.

This paper moves on this background to inspect the determinants of the education-job mismatch faced by PhD graduates. In particular, it focuses on the role of spatial mobility in favouring a potential match. Indeed, despite this topic has been extensively investigated on university graduates, few studies concentrate on PhD holders. Thus, using the most recent wave of the Italian Survey on the employability of PhD holders, provided by ISTAT in 2018, we evaluate the role of different flows of migration on overeducation, overskilling and job satisfaction.

Our results confirm our research questions. Indeed, we find a positive role of spatial mobility on the education-job match, especially in the form of long-distance migration in the early stage of the education path (i.e. from high school to university). Moreover, the analysis reveals a significant gap between the Italian and the foreign labour market under all the three aspects of educational mismatching under investigation (i.e. overeducation, overskilling, satisfaction). People investing in international migration are more likely to reap the rewards to education in terms of education-job matching opportunities. Unexpectedly, we do not find evidence on the well-known Italian North-South divide.

Unfortunately, despite women represent the majority in the interviewed population, it still emerges a significant gender gap from our analysis. This irrespective of being married and having children. This result seems to be dramatically robust in our study.

From a policy standpoint, our results underline the need to favour the creation of job opportunities that fit the level of knowledge, competencies and skills of PhD holders. Since the investment in human capital has always been underlined as a crucial determinant of innovation, technological improvement and, thus, growth, this may be the way to avoid the brain drain and the productive decline of the country.

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Table 1. List of Variables

Dependent Variables		
	Migration	Dummy variable equals to 1 if the individual migrates at least once in his life and 0 otherwise.
	Overeducation	Dummy variable equals to 1 if the PhD title was not a requirement to get the job and 0 otherwise.
	Overskilling	Dummy variable equals to 1 if the PhD title was not useful or needed to carry out the job and 0 otherwise.
	Satisfaction	Dummy variable equals to 1 if respondents are satisfied with the use of PhD skills in carrying out the job and 0 otherwise.
Individual-level Variables (X)		
	Age	Categorical variable indicating the age of the PhD holders: 1= age $\leq$ 28 (*reference*); 2= 29 $\leq$ age $\leq$ 30; 3= 31 $\leq$ age $\leq$ 34; 4= age $\geq$ 35 years.
	Female	Dummy equals to 1 if the respondent is a female and 0 otherwise.
	Married	Dummy equals to 1 if the respondent is married and 0 otherwise.
	Children	Dummy equals to 1 if the respondent has at least 1 child and 0 otherwise.
	Parents Education	Dummy variable equals to 1 if parents' educational level is high school, degree or more and 0 otherwise.
	Parents Occupation	Dummy variable equals to 1 if both parents are employed and 0 otherwise.
Job-Related variables (Z)		
	Job Contract	Categorical variable indicating the type of job contract 1= permanent contract (*reference*); 2= fixed-term contract; 3= atypical contract (occasional employment, self-employed, research grant).
	Experience	Categorical variable indicating the years of experience in the job. 0 year =2018-2018 (*reference*); 1 year= 2018-2017; 2 years= 2018-2016; 3 years= 2018-2015; 4 years= 2018-2014; 5 years= 2018-2013; 6 years= 2018-2012.
	Sector of Activity	Categorical variable indicating the sector of activity: 1= R&D in public administrations (*reference*); 2= R&D in private institution; 3= Industry; 4= University; 5= Non-academic education; 6= Agriculture and other services.

Education-related variables (T)		
	Specialization	Categorical variable indicating the PhD specialization: 1= LS - Science and medicine (*reference*) 2= PE - Physics and engineering; 3= SH - Social sciences.
	Year of PhD	Dummy variable equals to 1 if the PhD was completed in 2012 and 0 otherwise.
	Scholarship	Dummy variable equals to 1 if benefited from a scholarship during the PhD and 0 otherwise.
	Degree Grade	Categorical variable indicating the degree grade: 1= grade $\leq$104 (*reference*); 2= 105 $\leq$grade $\leq$ 109; 3= grade $\geq$ 110.
	Teaching	Dummy variable equals to 1 if the respondent did some teaching activity during the PhD and 0 otherwise.
	Visiting	Dummy variable assuming value 1 if the respondents spend a research period abroad during PhD and 0 otherwise.
	In time	Dummy variable assuming value 1 if PhD was finished in time.
Migration-related variables		
	High school to University	Categorical variable indicating migration from high-school to degree 1= no migration (*reference*); 2= inside the NUTS1; 3= outside the NUTS1.
	University to PhD	Categorical variable indicating migration from university to PhD: 1= no migration (*reference*); 2= inside the NUTS1; 3= outside the NUTS1.
	PhD to Labour Market	Categorical variable indicating migration from PhD to labour market: 1= no migration (*reference*); 2= inside the NUTS1; 3= outside the NUTS1; 4= migration abroad.
Regional Labour market (R)	Labour Market Dummies	Dummies indicating where the respondent works: Foreign labour market (*reference*) and NUTS1 Regions.
Inverse Mill's ratio	IMR	Inverse Mill's ratio from equation 1 (migration decision)

Table 2. Summary Statistics

Variables	*Frequency*	*%.*
Migration	5,796	54,31%
Overeducation	1,984	18.59%
Overskilling	5,333	49.97 %
Satisfaction	7,814	73.21%
Age		
Age ≤28	2,056	19.26%
29≤Age≤30	3,611	33.83%
31≤Age≤34	3,303	30.95%
Age ≥ 35	1,703	15.96%
Female	5,665	53.08%
Married	4,625	43.33%
Children	3,501	32.80%
Parents Education	8,542	80.52%
Parents Occupation	5,656	52.99%
Job Contract		
Permanent	3,834	35.92%
Fixed-Term Contract	2,736	25.63%
Atypical Contract	4,103	38.44%
Experience		
0 Year	852	7.98%
1 Years	3,217	30.14%
2 Years	2,088	19.56%
3 Years	1,783	16.71%
4 Years	1,023	9.58%
5 Years	701	6.57%
6 Years	1,009	9.45%
Sector of Activity		
R&D In Public Admin.	1,060	9.97%
R&D In Private Institution	583	5.49%
Industry	1,010	9.50%
University	2,975	27.99%
Non-Accademic Education	1,789	16.83%
Agriculture And Other Services	3,211	30.21%

Specialization		
LS (Science And Medicine)	3,282	30.75%
PE (Physics And Engineering)	4,070	38.13%
SH (Social Sciences)	3,321	31.12%
Year of PhD		
2014	4,725	44.27%
2012	5,948	55.73%
Scholarship	8,491	79.56%
Degree Grade		
Grade≤104	1,225	11.48%
105≤Grade≤109	1,383	12.96%
Grade ≥110	8,065	75.56%
Teaching	7,565	70.88%
Visiting	5,186	48.59%
In time	8,986	84.19%
Migration: **High school to University**		
No Migration	8,287	77.64%
Inside NUTS1	481	4.51%
Outside NUTS1	1,905	17.85%
Migration: **University to PhD**		
No Migration	8,012	75.07%
Inside NUTS1	706	6.61%
Outside NUTS1	1,955	18.32%
Migration: **PhD to Labour Market**		
No Migration	6,045	56.64%
Inside NUTS1	694	6.50%
Outside NUTS1	1,913	17.94%
Labour Market		
Foreign	2,021	18,94%
North-West	2,344	21.96%
North-East	1,693	15.86%
Centre	2,433	22.80%
South	2,182	20.44%

Table 3. Migration Flows

High School to University	*University to PhD*	*PhD to Labour Market*	*Frequency*	*%.*
No	No	No	4,877	45,69%
Yes	No	No	694	6.50%
No	Yes	No	274	2.57%
No	No	Yes	1,837	17.21%
Yes	Yes	Yes	888	8.32%
Yes	Yes	No	200	1.87%
Yes	No	Yes	604	5.66%
No	Yes	Yes	1,299	12.17%

Table 4. Selection equation for Migration – Probit model

Variables	*Migration*
Female	-0.0698***
	(0.00968)
	0.0346***
Parents Education	(0.0128)
	0.0304***
Parents Occupation	(0.0101)
Age Graduation	
Age ≤ 24	*Reference*
25 ≤ Age ≤ 26	-0.0292**
	(0.0117)
27 ≤ Age ≤ 30	-0.0830***
	(0.0141)
Age ≥ 31	-0.164***
	(0.0241)
Regional Dummies	
Piemonte	*Reference*
Valle d'Aosta	/
Lombardia	-0.0513**
	(0.0234)
Trentino	0.288***
	(0.0423)
Veneto	0.0746***
	(0.0265)
Friuli	0.149***
	(0.0364)
Liguria	0.0962**
	(0.0380)
Emilia	0.0482*
	(0.0283)
Toscana	-0.0747***
	(0.0268)

Umbria	0.155***
	(0.0393)
Marche	0.161***
	(0.0337)
Lazio	-0.00519
	(0.0241)
Abbruzzo	0.155***
	(0.0361)
Molise	0.402***
	(0.0462)
Campania	0.0977***
	(0.0247)
Puglia	0.0992***
	(0.0262)
Basilicata	0.360***
	(0.0405)
Calabria	0.254***
	(0.0289)
Sicilia	0.0907***
	(0.0256)
Sardegna	0.0231
	(0.0346)
Mcfadden	0.037
Mcfadden (Adjusted)	0.034
Percentage of Correctly Predicted	60%
Observations	10,136

Table 5. Education-job mismatch - Multivariate Probit model

Variables	*Overeducation* (1)	*Overskilling* (2)	*Satisfaction* (3)
Age			
Age ≤ 28	*Reference*	*Reference*	*Reference*
29 ≤ Age ≤ 30	0.177***	0.0993**	-0.103**
	(0.0516)	(0.0446)	(0.0420)
31 ≤ Age ≤ 34	0.298***	0.214***	-0.195***
	(0.0537)	(0.0478)	(0.0446)
Age ≥ 35	0.308***	0.142**	-0.175***
	(0.0645)	(0.0601)	(0.0552)
Female	0.182***	0.139***	-0.121***
	(0.0361)	(0.0334)	(0.0310)
Married	-0.0352	0.0427	0.0438
	(0.0386)	(0.0361)	(0.0335)
Children	0.00602	-0.0317	0.00670
	(0.0409)	(0.0388)	(0.0358)
Parents Education	-0.0839**	0.0138	-0.0444
	(0.0417)	(0.0396)	(0.0366)
Parents Occupation	-0.0642*	0.00422	0.0564*
	(0.0341)	(0.0317)	(0.0293)
Job Contract			
Permanent Contract	*Reference*	*Reference*	*Reference*
Fixed-Term Contract	-0.0767*	-0.193***	-0.0540
	(0.0451)	(0.0417)	(0.0383)
Atypical Contract	-0.0478	-0.309***	-0.0223
	(0.0413)	(0.0395)	(0.0369)
Experience			
0 Year	*Reference*	*Reference*	*Reference*
1 Year	0.0544	0.0490	-0.129**
	(0.0696)	(0.0612)	(0.0581)
2 Years	0.181**	0.0324	-0.169***
	(0.0722)	(0.0641)	(0.0609)
3 Years	0.148**	0.0718	-0.142**
	(0.0734)	(0.0657)	(0.0621)

4 Years	0.125	0.0987	0.000527
	(0.0798)	(0.0733)	(0.0693)
5 Years	0.264***	0.136*	-0.0407
	(0.0879)	(0.0817)	(0.0772)
6 Years	0.191**	0.225***	-0.142**
	(0.0821)	(0.0750)	(0.0708)
Sector of Activity			
R&D In Public Administration	*Reference*	*Reference*	*Reference*
R&D In Private Institution	0.248**	0.568***	-0.237***
	(0.126)	(0.0779)	(0.0846)
Industry	1.361***	1.604***	-0.910***
	(0.0995)	(0.0730)	(0.0726)
University	-0.0557	-0.182***	0.0455
	(0.0997)	(0.0636)	(0.0640)
Non-Accademic Education	0.788***	1.845***	-0.913***
	(0.0966)	(0.0685)	(0.0674)
Agriculture And Other Services	1.523***	1.854***	-1.054***
	(0.0896)	(0.0610)	(0.0613)
Specialization			
LS	*Reference*	*Reference*	*Reference*
PE	-0.00634	0.0449	-0.0488
	(0.0423)	(0.0387)	(0.0359)
SH	0.121***	0.0395	-0.00754
	(0.0429)	(0.0407)	(0.0374)
Year of PhD	0.0468	-0.00607	-0.0516*
	(0.0364)	(0.0336)	(0.0310)
Scholarship	-0.0736*	-0.0223	0.0862**
	(0.0396)	(0.0381)	(0.0347)
Degree Grade			
Grade ≤ 104	*Reference*	*Reference*	*Reference*
105 ≤ Grade ≤ 109	-0.0530	-0.0997	-0.00863
	(0.0643)	(0.0622)	(0.0574)
Grade ≥110	-0.100*	-0.0780	-0.0192
	(0.0538)	(0.0518)	(0.0480)
Teaching	-0.0181	-0.00397	0.0858***

	(0.0367)	(0.0340)	(0.0313)
Visiting	-0.152***	-0.0857***	0.0667**
	(0.0347)	(0.0320)	(0.0296)
In Time	-0.0855*	-0.0227	0.00507
	(0.0449)	(0.0434)	(0.0397)
Labour Market			
Foreign	*Reference*	*Reference*	*Reference*
North-West	0.350***	0.370***	-0.113**
	(0.0669)	(0.0549)	(0.0521)
North-East	0.455***	0.384***	-0.125**
	(0.0701)	(0.0584)	(0.0556)
Centre	0.386***	0.341***	-0.151***
	(0.0667)	(0.0552)	(0.0522)
South And Island	0.389***	0.288***	-0.115**
	(0.0731)	(0.0620)	(0.0585)
Migration	-0.0770**	-0.121***	0.0359
	(0.0373)	(0.0354)	(0.0327)
IMR	-0.142	0.00959	-0.0786
	(0.115)	(0.107)	(0.0986)
Constant	-2.027***	-1.289***	1.565***
	(0.199)	(0.171)	(0.161)
Correlation of Error Terms	0.520***	-0.572***	-0.613***
	(0.0228)	(0.0202)	(0.0213)
Observations	10,094	10,094	10,094

NOTE: Estimate Coefficients by Multivariate Probit. Standard Errors In Parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 6. Education-job mismatch and migration flows - Multivariate Probit model

Variables	*Overeducation* (1)	*Overskilling* (2)	*Satisfaction* (3)
Age			
Age ≤ 28	*Reference*	*Reference*	*Reference*
29 ≤ Age ≤ 30	0.179***	0.102**	-0.107**
	(0.0517)	(0.0446)	(0.0421)
31 ≤ Age ≤ 34	0.295***	0.216***	-0.203***
	(0.0539)	(0.0478)	(0.0447)
Age ≥ 35	0.306***	0.131**	-0.172***
	(0.0647)	(0.0603)	(0.0554)
Female	0.188***	0.137***	-0.122***
	(0.0363)	(0.0335)	(0.0312)
Married	-0.0299	0.0459	0.0301
	(0.0387)	(0.0361)	(0.0334)
Children	-0.00179	-0.0375	0.0119
	(0.0410)	(0.0388)	(0.0358)
Parents Education	-0.0883**	0.00724	-0.0449
	(0.0418)	(0.0396)	(0.0367)
Parents Occupation	-0.0582*	0.00458	0.0552*
	(0.0342)	(0.0318)	(0.0293)
Job Contract			
Permanent Contract	*Reference*	*Reference*	*Reference*
Fixed-Term Contract	-0.0856*	-0.196***	-0.0525
	(0.0452)	(0.0417)	(0.0384)
Atypical Contract	-0.0426	-0.314***	-0.0202
	(0.0414)	(0.0395)	(0.0369)
Experience			
0 Year	*Reference*	*Reference*	*Reference*
1 Year	0.0600	0.0551	-0.122**
	(0.0697)	(0.0611)	(0.0581)
2 Years	0.184**	0.0363	-0.162***
	(0.0722)	(0.0640)	(0.0609)
3 Years	0.151**	0.0767	-0.139**
	(0.0734)	(0.0655)	(0.0621)

4 Years	0.138*	0.120	-0.0141
	(0.0799)	(0.0731)	(0.0692)
5 Years	0.275***	0.164**	-0.0628
	(0.0881)	(0.0815)	(0.0772)
6 Years	0.193**	0.217***	-0.125*
	(0.0822)	(0.0750)	(0.0708)
Sector of Activity			
R&D In Public Administration	*Reference*	*Reference*	*Reference*
R&D In Private Institution	0.245*	0.543***	-0.206**
	(0.127)	(0.0779)	(0.0845)
Industry	1.368***	1.589***	-0.879***
	(0.0999)	(0.0729)	(0.0726)
University	-0.0536	-0.186***	0.0557
	(0.100)	(0.0635)	(0.0638)
Non-Accademic Education	0.789***	1.842***	-0.903***
	(0.0970)	(0.0685)	(0.0673)
Agriculture And Other Services	1.525***	1.839***	-1.029***
	(0.0901)	(0.0609)	(0.0611)
Specialization			
LS	*Reference*	*Reference*	*Reference*
PE	-0.00529	0.0497	-0.0530
	(0.0424)	(0.0387)	(0.0359)
SH	0.118***	0.0481	-0.0149
	(0.0432)	(0.0409)	(0.0376)
Year of Phd	0.0452	-0.00814	-0.0528*
	(0.0365)	(0.0336)	(0.0310)
Scholarship	-0.0754*	-0.0299	0.0919***
	(0.0396)	(0.0381)	(0.0347)
Degree Grade			
Grade ≤ 104	*Reference*	*Reference*	*Reference*
105 ≤ Grade ≤ 109	-0.0512	-0.111*	0.00295
	(0.0645)	(0.0623)	(0.0575)
Grade ≥110	-0.0980*	-0.0889*	-0.00538
	(0.0539)	(0.0519)	(0.0480)
Teaching	-0.0188	-0.00289	0.0802**

	(0.0368)	(0.0341)	(0.0314)
Visiting	-0.152***	-0.0791**	0.0624**
	(0.0348)	(0.0320)	(0.0296)
In Time	-0.0924**	-0.0159	-0.00675
	(0.0449)	(0.0433)	(0.0397)
***Migration*: High School to University**			
No Migration	*Reference*	*Reference*	*Reference*
Migration Inside The Nuts1	0.0107	-0.0592	0.0532
	(0.0780)	(0.0747)	(0.0688)
Migration Outside The Nuts1	-0.113**	-0.0290	-0.00540
	(0.0518)	(0.0470)	(0.0435)
***Migration*: University to PhD**			
No Migration	*Reference*	*Reference*	*Reference*
Migration Inside The Nuts1	0.164**	-0.108	-0.00626
	(0.0741)	(0.0690)	(0.0644)
Migration Outside The Nuts1	0.0215	-0.0259	0.0573
	(0.0535)	(0.0479)	(0.0451)
***Migration*: PhD to Labour Market**			
No Migration	*Reference*	*Reference*	*Reference*
Migration Inside The Nuts1	-0.0222	0.0180	0.0252
	(0.0728)	(0.0690)	(0.0646)
Migration Outside The Nuts1	-0.0739	-0.0947**	-0.0152
	(0.0484)	(0.0449)	(0.0417)
Labour Market			
Foreign	*Reference*	*Reference*	*Reference*
North-West	0.404***	0.444***	-0.113**
	(0.0680)	(0.0552)	(0.0525)
North-East	0.496***	0.459***	-0.130**
	(0.0699)	(0.0580)	(0.0550)
Centre	0.436***	0.408***	-0.152***
	(0.0666)	(0.0546)	(0.0516)
South And Island	0.443***	0.382***	-0.131**
	(0.0690)	(0.0572)	(0.0538)
IMR	-0.127	0.0379	-0.105
	(0.117)	(0.109)	(0.100)

Constant	-2.113***	-1.390***	1.593***
	(0.193)	(0.166)	(0.156)
Correlation of Error Terms	0.505***	-0.556***	-0.620***
	(0.0226)	(0.0202)	(0.0215)
Observations	10,094	10,094	10,094

Note: Estimate Coefficients by Multivariate Probit. Standard Errors in Parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Online Appendix A

Table A1. Education-job mismatch and migration flows- Multivariate Probit model.

The sub-population of non-academic workers

Variables	***Overeducation*** **(1)**	***Overskilling*** **(2)**	***Satisfaction*** **(3)**
Age			
Age ≤ 28	*Reference*	*Reference*	*Reference*
29 ≤ Age ≤ 30	0.166***	0.0922*	-0.0749
	(0.0542)	(0.0499)	(0.0467)
31 ≤ Age ≤ 34	0.240***	0.134**	-0.131***
	(0.0567)	(0.0536)	(0.0495)
Age ≥ 35	0.271***	0.0646	-0.150**
	(0.0681)	(0.0672)	(0.0609)
Female	0.175***	0.136***	-0.126***
	(0.0385)	(0.0375)	(0.0345)
Married	-0.0444	0.0585	0.0282
	(0.0409)	(0.0402)	(0.0368)
Children	0.0172	-0.0312	0.0336
	(0.0434)	(0.0433)	(0.0393)
Parents Education	-0.0867**	0.0197	-0.0261
	(0.0442)	(0.0440)	(0.0403)
Parents Occupation	-0.0647*	0.0282	0.0446
	(0.0362)	(0.0355)	(0.0325)
Job Contract			
Permanent Contract	*Reference*	*Reference*	*Reference*
Fixed-Term Contract	-0.00734	-0.0949**	-0.139***
	(0.0476)	(0.0459)	(0.0417)
Atypical Contract	0.0452	-0.278***	-0.0497
	(0.0436)	(0.0433)	(0.0403)
Experience			
0 Year	*Reference*	*Reference*	*Reference*
1 Year	0.0732	0.0358	-0.102
	(0.0749)	(0.0705)	(0.0664)
2 Years	0.180**	-0.0105	-0.113

	(0.0778)	(0.0736)	(0.0695)
3 Years	0.155**	0.0506	-0.0837
	(0.0786)	(0.0749)	(0.0705)
4 Years	0.142*	0.0692	0.0258
	(0.0846)	(0.0817)	(0.0765)
5 Years	0.287***	0.0960	-0.0235
	(0.0936)	(0.0916)	(0.0859)
6 Years	0.131	0.138	-0.0447
	(0.0882)	(0.0854)	(0.0797)
Sector of Activity			
R&D In Public Administration	*Reference*	*Reference*	*Reference*
R&D In Private Institution	0.276**	0.581***	-0.255***
	(0.126)	(0.0781)	(0.0846)
Industry	1.423***	1.623***	-0.942***
	(0.0998)	(0.0736)	(0.0735)
Non-Accademic Education	0.822***	1.852***	-0.915***
	(0.0974)	(0.0702)	(0.0691)
Agriculture And Other Services	1.573***	1.883***	-1.079***
	(0.0897)	(0.0615)	(0.0619)
Specialization			
LS	*Reference*	*Reference*	*Reference*
PE	0.00553	0.111***	-0.0774*
	(0.0446)	(0.0429)	(0.0395)
SH	0.136***	0.119**	-0.0291
	(0.0459)	(0.0463)	(0.0418)
Year of Phd	0.0430	0.00283	-0.0575*
	(0.0385)	(0.0375)	(0.0343)
Scholarship	-0.0520	-2.34e-05	0.0681*
	(0.0420)	(0.0424)	(0.0382)
Degree Grade			
Grade ≤ 104	*Reference*	*Reference*	*Reference*
105 ≤ Grade ≤ 109	-0.0500	-0.0804	-0.0117
	(0.0678)	(0.0686)	(0.0627)
Grade ≥110	-0.114**	-0.0840	0.00206
	(0.0568)	(0.0576)	(0.0528)

Teaching	-0.0155	0.00161	0.0864**
	(0.0388)	(0.0376)	(0.0345)
Visiting	-0.139***	-0.0424	0.0506
	(0.0367)	(0.0359)	(0.0328)
In Time	-0.0833*	0.0195	-0.0224
	(0.0477)	(0.0482)	(0.0437)
***Migration*: High School to University**			
No Migration	*Reference*	*Reference*	*Reference*
Migration Inside The Nuts1	0.00299	0.0207	-0.0161
	(0.0824)	(0.0825)	(0.0754)
Migration Outside The Nuts1	-0.139**	-0.0291	0.00979
	(0.0547)	(0.0522)	(0.0484)
***Migration*: University to PhD**			
No Migration	*Reference*	*Reference*	*Reference*
Migration Inside The Nuts1	0.124	-0.156**	0.0420
	(0.0801)	(0.0779)	(0.0738)
Migration Outside The Nuts1	0.0351	-0.0294	0.0286
	(0.0564)	(0.0534)	(0.0500)
***Migration*: PhD to Labour Market**			
No Migration	*Reference*	*Reference*	*Reference*
Migration Inside The Nuts1	0.00774	-0.00735	0.0183
	(0.0765)	(0.0759)	(0.0703)
Migration Outside The Nuts1	-0.0993*	-0.149***	0.0118
	(0.0507)	(0.0492)	(0.0453)
Labour Market			
Foreign	*Reference*	*Reference*	*Reference*
North-West	0.396***	0.539***	-0.195***
	(0.0722)	(0.0632)	(0.0612)
North-East	0.485***	0.526***	-0.200***
	(0.0743)	(0.0662)	(0.0637)
Centre	0.413***	0.448***	-0.225***
	(0.0706)	(0.0620)	(0.0598)
South And Island	0.430***	0.423***	-0.213***
	(0.0731)	(0.0647)	(0.0619)
IMR	-0.135	-0.0320	-0.0252

	(0.124)	(0.122)	(0.111)
Constant	-2.154***	-1.545***	1.629***
	(0.202)	(0.185)	(0.172)
Correlation of Error Terms	0.521***	-0.591***	-0.607***
	(0.0255)	(0.0219)	(0.0236)
Observations	7,341	7,341	7,341

Note: Estimate Coefficients by Multivariate Probit. Standard Errors In Parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table A2. Education-job mismatch and migration flows- Multivariate Probit model.

The sub-population of Italian market workers

Variables	***Overeducation*** (1)	***Overskilling*** (2)	***Satisfaction*** (3)
Age			
Age ≤ 28	*Reference*	*Reference*	*Reference*
29 ≤ Age ≤ 30	0.160***	0.0761	-0.113**
	(0.0550)	(0.0496)	(0.0464)
31 ≤ Age ≤ 34	0.254***	0.172***	-0.172***
	(0.0571)	(0.0525)	(0.0489)
Age ≥ 35	0.274***	0.103	-0.173***
	(0.0676)	(0.0644)	(0.0589)
Female	0.182***	0.149***	-0.136***
	(0.0381)	(0.0362)	(0.0336)
Married	-0.0437	0.0613	0.0179
	(0.0406)	(0.0391)	(0.0360)
Children	0.0181	-0.0323	0.00929
	(0.0427)	(0.0413)	(0.0380)
Parents Education	-0.0962**	0.0138	-0.0507
	(0.0434)	(0.0422)	(0.0390)
Parents Occupation	-0.0617*	0.00899	0.0582*
	(0.0360)	(0.0343)	(0.0316)
Job Contract			
Permanent Contract	*Reference*	*Reference*	*Reference*
Fixed-Term Contract	-0.0673	-0.167***	-0.0959**
	(0.0477)	(0.0451)	(0.0413)
Atypical Contract	-0.0437	-0.278***	-0.0366
	(0.0433)	(0.0428)	(0.0398)
Experience			
0 Year	*Reference*	*Reference*	*Reference*
1 Year	0.0764	0.0352	-0.154**
	(0.0731)	(0.0655)	(0.0629)
2 Years	0.198***	0.0445	-0.228***
	(0.0760)	(0.0690)	(0.0661)
3 Years	0.175**	0.0741	-0.163**

	(0.0773)	(0.0709)	(0.0676)
4 Years	0.204**	0.156**	-0.0773
	(0.0835)	(0.0787)	(0.0745)
5 Years	0.313***	0.167*	-0.0833
	(0.0927)	(0.0882)	(0.0836)
6 Years	0.239***	0.208***	-0.173**
	(0.0859)	(0.0805)	(0.0762)
Sector of Activity			
R&D In Public Administration	*Reference*	*Reference*	*Reference*
R&D In Private Institution	0.255*	0.573***	-0.248**
	(0.135)	(0.0881)	(0.0983)
Industry	1.357***	1.635***	-0.953***
	(0.107)	(0.0813)	(0.0820)
University	-0.0314	-0.183***	0.0555
	(0.106)	(0.0703)	(0.0738)
Non-Accademic Education	0.746***	1.852***	-0.918***
	(0.102)	(0.0738)	(0.0748)
Agriculture And Other Services	1.524***	1.842***	-1.081***
	(0.0957)	(0.0670)	(0.0693)
Specialization			
LS	*Reference*	*Reference*	*Reference*
PE	0.0142	0.0724*	-0.0756*
	(0.0445)	(0.0419)	(0.0388)
SH	0.118***	0.0449	-0.0331
	(0.0449)	(0.0435)	(0.0399)
Year Of Phd	0.0175	-0.0190	-0.0315
	(0.0383)	(0.0362)	(0.0334)
Scholarship	-0.0720*	-0.0437	0.0828**
	(0.0412)	(0.0405)	(0.0370)
Degree Grade			
Grade $\leq$ 104	*Reference*	*Reference*	*Reference*
105 $\leq$ Grade $\leq$ 109	-0.0425	-0.124*	0.0387
	(0.0670)	(0.0661)	(0.0609)
Grade $\geq$110	-0.101*	-0.0946*	0.0198
	(0.0561)	(0.0551)	(0.0508)

Teaching	-0.0210	-0.0212	0.102***
	(0.0388)	(0.0369)	(0.0339)
Visiting	-0.134***	-0.0756**	0.0618*
	(0.0365)	(0.0344)	(0.0318)
In Time	-0.0860*	-0.000580	-0.00526
	(0.0475)	(0.0467)	(0.0429)
***Migration*: High School to University**			
No Migration	*Reference*	*Reference*	*Reference*
Migration Inside The Nuts1	0.0217	-0.0324	-0.00281
	(0.0825)	(0.0815)	(0.0747)
Migration Outside The Nuts1	-0.0970*	-0.00422	-0.00563
	(0.0557)	(0.0527)	(0.0485)
***Migration*: University to PhD**			
No Migration	*Reference*	*Reference*	*Reference*
Migration Inside The Nuts1	0.168**	-0.181**	-0.0384
	(0.0795)	(0.0762)	(0.0716)
Migration Outside The Nuts1	-0.00251	-0.0833	0.0854*
	(0.0583)	(0.0543)	(0.0507)
***Migration*: PhD to Labour Market**			
No Migration	*Reference*	*Reference*	*Reference*
Migration Inside The Nuts1	-0.0397	0.0464	0.0751
	(0.0746)	(0.0711)	(0.0670)
Migration Outside The Nuts1	-0.0726	-0.0729	-0.00882
	(0.0495)	(0.0465)	(0.0431)
Labour Market			
North-West	*Reference*	*Reference*	*Reference*
North-East	0.0894*	-0.00342	0.00147
	(0.0533)	(0.0504)	(0.0469)
Centre	0.0356	-0.0326	-0.0371
	(0.0470)	(0.0446)	(0.0413)
South And Island	0.0453	-0.0706	-0.0156
	(0.0533)	(0.0508)	(0.0468)
IMR	-0.154	0.0312	-0.0603
	(0.123)	(0.118)	(0.108)
Constant	-1.670***	-0.947***	1.499***

	(0.203)	(0.181)	(0.171)
Correlation of Error Terms	0.504***	-0.545***	-0.629***
	(0.0242)	(0.0208)	(0.0231)
Observations	8,424	8,424	8,424

Note: Estimate Coefficients by Multivariate Probit. Standard Errors In Parentheses; *** p<0.01, ** p<0.05, * p<0.1.