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Should I stay or should I go?
Migration and job-skills mismatch among Italian doctoral recipients

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Abstract

Finding a non-academic job in line with both doctoral graduates' degree and acquired know-how can be difficult because of insufficient demand for R&D skills in public administration and private enterprise and/or because of the lack of matching between the existing demand and the Ph.D. holders' specialization. The aim of this paper is to test whether migrating from some regions may improve job-education matching in Italy. The econometric strategy takes into account Ph.D. holders' self-selection into non-academic employment as well as the endogeneity of the migration choice. Results demonstrate that migration seems to facilitate the possibility of finding better job opportunities. More specifically, only migration within the regions of the centre and north of Italy seems to improve job-education matching.

Keywords: Ph.D. holders, job-education mismatch, migration

JEL codes: J61, J24

1. Introduction

Investment in doctoral education has been suggested as being crucial in current knowledge economies, where Ph.D.-level Research and Development (R&D) skills are considered drivers of private returns – which might take the form of higher wages (Mellors-Bourne et al., 2013; Mertens and Rübken, 2013) – as well as of societal level returns that originate from the creation of innovations and the boosting of productivity that Ph.D. holders might stimulate (Auriol et al., 2010, Casey, 2009). In European countries, the intersectoral mobility of Ph.D. holders (i.e. their employment in non-academic sectors) is both necessary – given the notable increase in the supply of doctorate holders observed over recent years (OECD, 2016), which makes it impossible for all of them to achieve academic positions – and strongly advocated, because of the positive knowledge transfer effects that it is supposed to generate (Vandevelde, 2014). Nevertheless, recent research reveals that in some European countries Ph.D. holders face remarkable difficulties in finding a non-academic job well-matched with their educational and skills background (Ermini et al., 2017a; Gaeta et al., 2017; Boulos, 2016; Di Paolo and Mañé, 2016; Gaeta, 2015; van de Schoot et al., 2012; Lee et al., 2010). Since such difficulties might compromise the benefits arising from Ph.D. education, the inspection of factors that might foster or hamper job/education matching among Ph.D. holders has to be considered as being particularly valuable.

The literature focusing on job/education matching among graduates highlights that it crucially depends on the context where individuals live. Seminal contributions have suggested that education payoff depends on the degree of technological progress observed where one lives (Nelson and Phelps, 1966). More recently, scholars have highlighted that the availability of matched employment opportunities for graduates depends on macroeconomic conditions (Borgna et al., 2018; Summerfield and Theodossiou, 2017) and on the level and type of sectorial specialization of the economy (McGuinness et al., 2018). In line with this perspective, the literature suggests that spatial flexibility allows better job/education matching since migrating allows workers to gain access to destinations where, compared to the place of origin, there are a higher number of available employment opportunities that are adequate for their educational background (Büchel and Van Ham, 2003; van Ham et al., 2001).

This paper aims to empirically verify whether such a positive impact of migration on job/education matching is also observed in the case of Ph.D. holders. An expanding literature examines researchers' migration trends and the determinants of mobility choices (Bauder, 2015; Morano-Foadi, 2005). Nevertheless, a detailed investigation specifically focused on the link between migration and

job/education matching among doctoral recipients has not been provided yet. This is surprising, since studying the geography of doctoral recipients' job/education matching is essential for mapping knowledge flows generated by migration (Iammarino and Martinelli, 2015) and for designing effective policies that might support the full exploitation of the Ph.D. holders' potential.

The analysis provided in this paper is focused on within-country migration and, more specifically, on Ph.D. recipients' cross-sectional micro data, recently collected in Italy through an extensive survey carried out by the Italian National Institute of Statistics (ISTAT). There are three reasons why this country is a valuable case study for examining the link between migration and job education/job mismatch among Ph.D. holders. First, there is a wide literature on Italian within-country regional disparities (Ercolano, 2012) that highlights the existence of wide cross-regional heterogeneity in terms of economic performance. On average, the Northern NUTS-1 Italian macro region (including the following NUTS-2 regions: Aosta Valley, Liguria, Lombardy, Piedmont, Emilia-Romagna, Friuli-Venezia Giulia, Trentino-Alto Adige/Südtirol, Veneto) reports the highest values of GDP per capita and R&D spending in the country, as well as the lowest unemployment rate. For the same indicators, the Southern part of the country (Abruzzo, Apulia, Basilicata, Calabria, Campania, Molise, Sicily and Sardinia), reports, on average, the lowest performances, while the NUTS 1 Centre macro region (Lazio, Marche, Tuscany, Umbria) lies somewhere between the two (Barrutia and Echebarria, 2010). Second, since there are a significant number of people migrating from Southern regions towards the Centre-North of the country and since the portion of those among them who are highly skilled has been increasing over recent years (Vecchione, 2018), the issue of the link between spatial mobility and job/education matching is particularly noteworthy in this country. Indeed, this issue has already been investigated by some recent contributions that focus specifically on university graduates (Iammarino and Marinelli, 2015; Croce and Ghignoni, 2015; Dotti et al., 2014; Devillanova, 2013), although a Ph.D.-focused analysis is still missing since previous studies have merely focused on the effect of spatial mobility on wages, without inspecting the issue of overeducation in particular (Ermini et al., 2017b). Third, recent studies report that Ph.D. holders in Italy quite frequently report overeducation, i.e. the usefulness of their degree to get the job they hold (Gaeta, 2015; Gaeta et al., 2017). Such evidence suggests that the investigation of factors that exert influence on Ph.D. holders' job/education matching probability in the Italian context is particularly interesting.

The ISTAT micro data are valuable for this study because they cover a big and highly representative sample of two cohorts of Ph.D. holders (graduates from 2008 and from 2010) and allow us to observe for each of the respondents a wide set of variables concerning the Ph.D. they achieved and the career

path they followed after the completion of doctoral education. The use of this data in order to analyse the existing link between migration and job/education mismatch has to deal with two main issues. On the one hand, the inspection of mismatch only makes sense when looking at those who are employed in the non-academic sector, since being employed as researchers in universities is surely in line with the doctoral education acquired. In this perspective, the empirical analysis has to take into account Ph.D. holders' self-selection into non-academic employment. On the other hand, Ph.D. holders' self-selection into migration is also an issue, since the migration choice might be driven by unobservable individual characteristics which are also connected to the overeducation condition. To deal with these two issues, the analysis relies on the methodological approach proposed by Arendt and Holm (2006), extending Heckman's sample selection model (Heckman, 1979), which has been applied in a previous study by Iammarino and Martinelli (2015) on the migration effect on overeducation among Italian university graduates. In our case, this approach consists of estimating three equations that respectively model: i) the migration choice; ii) the non-academic employment choice; iii) the job/education mismatch. When estimating the first two equations, an Inverse Mills Ratio (IMR) is calculated for each of the observations, and an IMR is used in the following step of the analysis with the aim of controlling for self-selection. By following such a procedure, the estimation of the third equation allows us to identify the effect of migration on overeducation by taking into account both self-selection into migration and self-selection into non-academic employment.

In line with the literature, results suggest that migration increases the likelihood of finding a job matched with the Ph.D.. Nevertheless, according to the econometric analyses, only migration within the regions of the Centre and North of Italy seems to exert a positive impact on job-education matching, while the same does not apply to migration originating from and directed towards Southern regions.

The remainder of the paper is organized as follows. Section 2 illustrates the data used in the empirical analysis. Section 3 provides an extensive description of the methodology adopted to carry out the analysis. Section 4 presents and discusses the results. Finally, section 5 concludes.

2. Data

Data are gathered from the second and most recent edition of the "Survey on employability of Ph.D. holders" ("Indagine sull'inserimento Professionale dei Dottori di Ricerca") carried out by ISTAT in 2014. This cross-sectional survey investigates the early stage career outcomes reported by individuals

who obtained a Ph.D. in Italy in 2008 and in 2010 and, therefore, were interviewed 4 and 6 years after graduation respectively.

The survey was designed in order to involve the entire population of Ph.D. recipients in the two considered cohorts. While part of this population did not answer, the final response rate reported by the survey, 72.64%, makes it highly representative of the population under scrutiny. The final sample includes 16,322 observations: 7,888 refer to Ph.D. holders who graduated in 2008 while 8,434 refer to those from the 2010 cohort.

A part of these observations is not included in our analysis. On the one hand, some of the interviewed Ph.D. holders declared themselves to be resident abroad. Since this paper aims to study within-country migration in the highly heterogeneous Italian context, those who migrated away from Italy were dropped from the analysis (1,944 out of a sample of 16,322, i.e. 11.92%). On the other hand, a limited number of respondents (1,116, i.e. 7% of the original sample) did not hold a job when interviewed. Obviously job/education matching cannot be observed for them, and they were therefore dropped from the analysis. In addition, 1,116 observations did not answer whether a Ph.D. was required for their job: thus, overeducation cannot be observed for them. As a consequence of these exclusions, the final sample under investigation includes 13,262 observations.

All the respondents who declared they held a job were asked one question that allows us to inspect their overeducation status, namely: “Was the Ph.D. title expressly required to obtain your current job position?” Three answers were possible: 1) *Yes, it was expressly required*; 2) *No, it was not but it was useful (i.e., it was important in the evaluation of qualification)*; 3) *No, it was not required and not useful*. Our analysis considers as well-matched all those respondents who hold a job that was specifically designed for Ph.D. holders. Therefore, we identify as overeducated all those who chose one of the latter two options. A dichotomous variable (labelled *overeducation*) was built that takes the value of one for the overeducated respondents and 0 otherwise. The overeducated workers in our sample are 9,633, i.e. 66.99% of the total, confirming the common finding in the literature about the importance and magnitude of the issue in Italy (Gaeta, 2013; Gaeta, 2017; Gaeta et al., 2017).

Since the objective of the paper is to investigate the link between migrating and being overeducated, the analysis required one variable that identifies those respondents who migrated after completing their Ph.D. For each observation the ISTAT survey allows us to observe the Italian region in which the Ph.D. was completed (i.e. the region in which the university where the Ph.D. student was enrolled is located), and the region where the Ph.D. holder officially lives at the time of the interview (4 or 6 years after the graduation). On the basis of such information we built a dichotomous

variable (labelled *migration*) which assumes a value of 1 when the region of residence is different from the region of graduation (i.e. if the respondent migrated after completing the Ph.D.), and a value of 0 if the interviewee still resides in the region in which the Ph.D. was completed. Overall, the share of migrants in our sample was 27.45%.

Table 1 provides information concerning the Italian macro-region where respondents achieved their Ph.D. (rows) and the one where they declared they worked when interviewed. Shares reported in the table are calculated by row. Data highlight that Northern regions show a remarkably higher capacity to retain Ph.D. students than Central and Southern ones. Migration trends highlighted by the table are definitely in line with those suggested by the literature on university graduates (Vecchione, 2018) and mostly follow the direction from South to Centre-North. On the other hand, migrations from Northern Italy towards Central and Southern regions are rare.

With the aim of investigating whether any specific migration direction exerts an influence on job/education matching, we constructed three dichotomous variables. The first variable is labelled *S-CN migration* and is equal to 1 if the individual migrated from a region in the South of the country towards a region located in the Centre-North and 0 otherwise. The second variable, labelled *CN-CN migration*, is equal to 1 if the migration has occurred from a Northern or Central region toward another region in the Centre or the North of the country. Finally, the third variable, labelled *S-S migration*, takes the value of 1 in case of migration among regions located in the Southern and Island parts of the country.

Alongside these variables, the ISTAT survey includes a wide set of data that are very valuable for our analysis insofar as they identify the features among respondents that might exert some influence on their migration choice and/or on the choice to be employed in the non-academic sector and/or on their overeducation status.

A first set (labelled X_1) includes two variables and allows us to identify the portion of the Ph.D. population which respondents belong to; these variables are one dummy (labelled *PhDin2010*) that takes the value of 1(0) for those belonging to the 2010 (2008) cohort under scrutiny, and one categorical variable that records respondents' field of Ph.D. specialization by distinguishing among Social Science and Humanities (ERCSH), Physical Sciences and Engineering (ERCPE) and Life Sciences.¹

¹ This is used as the reference modality and omitted from the regressions to avoid the dummy trap issue.

A second set of variables (X_2) observes respondents' basic socio-demographic conditions. This set includes gender, marital status, age (with dummies identifying those being 31, 32 or more than 32 years' old), and the highest level of education acquired by respondents' parents (*ParentDegrees*).

The third set of variables (X_3) observes respondents' migration choices before the completion of their Ph.D. studies. Dummies allow us to identify non-Italian respondents (*ForCit*), those who accomplished their Master's in a foreign country (*ForDegree*), those who migrated from one Italian region to another before their Ph.D. studies (*MigrBPhD*), and those who carried out a visiting period in a foreign country during their Ph.D. (*Visiting*).

The fourth set (X_4) allows us to observe features of the Ph.D. and previous studies carried out by respondents. First, a dichotomous variable (labelled *DegreeGrade>107*) is considered, which takes the value of 1 for those respondents who completed their Master's with a high grade (i.e. a grade higher than 107 where the minimum is 66 and maximum is 110 with laude). In addition, Ph.D.-related variables include the ERC sector that respondents' Ph.D. belongs to (*ERC SH*, *ERC PE*), one dummy identifying the Ph.D. cohort the respondent belongs to (*PhDin2010*), one dummy taking the value of one for those who benefitted from a scholarship (*Scholarship*) and another for those who taught lessons during their studies (*Teaching*). Furthermore, dummies allow us to identify those who completed their Ph.D. within the standard deadline, i.e. within three years (*InTime*). Three additional variables measure the number of papers (*Articles*), book chapters (*Chapters*) and monographs (*Monographs*) published by respondents since the end of their Ph.D.

Finally, the fifth set (X_5) includes variables that observe the main features of the job position held by respondents. On the basis of such information, we built one variable that assumes the value of 1 for those who got a job in the non-academic sector and 0 for those employed in universities (this variable is labelled *Non Academic*. This is important information for our analysis because people who work in the academic context cannot be considered as overeducated since a Ph.D. is a requirement for the university career in Italy.² Even if the great majority of the doctoral recipients in our sample (10,536) hold a non-academic job, such a sample selection needs to be controlled for in the empirical investigation and the approach adopted to take it into account will be discussed in the following

² It is worth noting that a few respondents declared they worked in academia and surprisingly reported they found themselves in an overeducation condition. These are likely to be technicians, assistants, administrators and other people pursuing non-academic careers within the universities. These observations have been dropped from the analysis to avoid biases in the data.

section. For those employed outside academia, one set of dummies observes the sector in which the Ph.D. graduate works, either Industry or Services (*DIndustry*, *DService*³). Furthermore, dummy variables observe features of the job that the respondents hold, such as working in the public sector (*DPA*), having a permanent contract (*PermanentContract*), having a fulltime contract (*Fulltime*) or being self-employed (*PIVA*).

Table 2 gives a full description of the variables, along with their labels, while Table 3 illustrates basic summary statistics calculated on our sample.

3. Methodology

Two issues have to be taken into account when studying the link between migration and overeducation by using the Ph.D. respondents' cross-sectional data presented in the previous section. First, Ph.D. holders' decision to migrate might be endogenous, since omitted variables could exist that explain both the treatment (migration) and the outcome (the overeducation status) considered by our analysis.

Second, as already highlighted in section 2, overeducation is only observed for those Ph.D. holders who hold non-academic jobs. Of course, the choice to work in the non-academic sector implies self-selection. As a consequence, in this case too there might exist unobserved variables that affect both the choice of being employed outside academia and the likelihood of falling into a condition of overeducation.

In a nutshell, since omitted factors that presumably affect the possibility of being overeducated might also be correlated with unobserved factors that affect the migration choice and the non-academic sector selection, standard regression techniques provide biased estimates.

In order to deal with such issues, our analysis relies on the methodology devised by Arendt and Holm (2006) that provides an extension of the Heckman correction method (Heckman, 1979). Such an empirical approach has already been adopted by Iammarino and Marinelli (2015) in studying the link between migration and overeducation among university graduates by simultaneously taking into account selection into employment and selection into migration. In the case of our analysis, since unemployment is definitely limited among Ph.D. holders, selection into employment is not a major issue. Nevertheless, the analysis has to deal with the issue of Ph.D. holders' selection into non-

³ In order to avoid the dummy trap econometric problem, we decided not to control for workers in the other sector, labelled by ISTAT as *Agricultural, Hunting and Fishing*.

academic job positions, the only ones that might result in an overeducation condition. Keeping this issue in mind, following Arendt and Holm (2006) and in line with Iammarino and Marinelli (2015), our model consists of three equations.

The first equation estimates respondents' probability of being migrants as follows:

$$Migration = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon \quad [1]$$

Migration is a dummy identifying those who moved from one Italian region to another after completing their Ph.D. studies, and X_1 , X_2 and X_3 are three vectors of covariates that include variables presented in the previous section. More specifically, these vectors allow us to identify the: i) portion of the Ph.D. population that respondents belong to (X_1); ii) respondents' basic socio-demographic conditions (X_2); and iii) respondents' migration choices before the completion of their Ph.D. studies (X_3). α , β_1 , β_2 and β_3 are parameters to be estimated while ε is the error term. A *probit* estimate of equation [1] allows us to calculate for each observation of the sample an Inverse Mills Ratio (IMR), which is the ratio of the probability that one respondent migrates over the cumulative distribution function of the distribution. Such an IMR is included as an explicative variable in the regression carried out in the second step of the analysis, with the aim of taking into account the endogeneity of the migration decision.

Equation [2] models respondents' choice of a non-academic working sector as follows:

$$Academy = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_4 + \beta_4 IMR + \varepsilon \quad [2]$$

where our dependent variable is the *Non Academic* dummy, and X_1 , X_2 and X_4 indicate the sets of covariates that respectively observe: i) the portion of the Ph.D. population that respondents belong to (X_1); ii) basic socio-demographic conditions (X_2); and iii) features of the Ph.D. and previous studies carried out by respondents (X_4). IMR represents the Inverse Mills Ratio calculated through the estimation of equation [1] and ε is the error term. The set of covariates considered in this equation differs from the one used in the migration equation (equation [1]) since, as suggested by Heckman (1979), for the health of the estimates it is necessary that in the selection equation there is at least one variable not present in the first-stage equation. α , β_1 , β_2 , β_3 and β_4 are parameters to be estimated while ε is the error term. The equation is estimated through the *probit* model.

Finally, equation [3] models overeducation as follows:

$$\text{Overeducation} = \alpha + \beta_1 \text{Migration} + \beta_2 X_1 + \beta_3 X_2 + \beta_4 X_5 + \beta_5 \text{IMR} + \varepsilon \quad [3]$$

where the *overeducation* dummy is the dependent variable, and X_1 , X_2 , X_5 are the sets of covariates considered with the aim of controlling for: i) the portion of the Ph.D. population that respondents belong to (X_1); ii) basic socio-demographic conditions (X_2); and iii) job-related variables (X_5). IMR represents the Inverse Mills Ratio calculated through the estimation of equation [2]. α , β_1 , β_2 , β_3 , β_4 and β_5 are the parameters to be estimated and ε is the error term. By following Iammarino and Marinelli (2015), this equation includes the *migration* dummy in order to study the effect of spatial (inter-regional) mobility on overeducation. In addition, in some of the specifications run, this equation was augmented by including those variables presented in the previous section that allow us to observe more details concerning respondents' migration: *S-CN Migration* (migration from the South toward the Centre-North of the country), *CN-CN Migration* (migration from the Centre-North toward the Centre-North), *S-S Migration* (migration from the South toward the South). Such variables were alternatively included in the equation with the aim of understanding whether the migration effect on overeducation is associated with any specific migration direction. As in the case of previous equations, equation [3] is estimated by relying on a *probit* model.

Computationally, the three steps of the analysis become two, since after the estimation of equation [1] and the related IMR, it is possible to estimate a *biprobit* with a sample selection that estimates equations [2] and [3] simultaneously. The standard Heckman procedure (of which this specification is an extension, as mentioned previously), assumes that the errors of the two equations are normally distributed, with zero mean and variance, and are correlated among themselves. The hypothesis that the two errors are not correlated has, then, to be tested with a specific Wald test. The rejection of the null hypothesis implies that in the model there is no problem of self-selection and the estimators are not biased. Instead, the impossibility of rejecting the null hypothesis evidences a problem of self-selection that needs a correction. When the value calculated for this test, which is conventionally reported as *athrho* is statistically significant, the Heckman selection model is appropriate.

Table 4 provides a summary of the variables used in each step of the analysis. As shown, variables that identify the portion of the Ph.D. population that respondents belong to (vector X_1) and those that are *socio-demographic* (vector X_2) are included in all the equations. Indeed, we assume that these variables have a significant correlation with respondents' migration choices, with their choice of pursuing a career outside academia, and with the job/education matching at the time of the interview. There is only one exception to this reasoning, which is represented by the variable *ParentDegree*. We

decided to include it only in the migration equation, since the level of education of the parents, and their overeducation, is expected to have an effect on their children's choice to migrate (Tani, 2017), and we do not expect it to have an impact on the choice to work in university or on the career pursued after the Ph.D. Nevertheless, our results still hold when this variable is used in all three equations (results are available upon request).

The other three sets of variables are: *Migration before Ph.D.* (ForCit, MigrBPhD, ForDegree, Visiting), which is included only in the migration equation since we expect this variable to affect the choice to migrate, but not to have an impact on career choices (both in field and in the final outcome); *Ph.D.-related variables* (InTime, Articles, Chapter, Monographies, Scholarship, Teaching, DegreeGrade>107) are variables expected to affect the likelihood of pursuing a career in academia after the Ph.D., aimed to measure the academic involvement of the student; finally *Job-related variables* (DIndustry, DService, DPA, Fulltime, Permanent Contract, PIVA) are variables that should have an impact on the choice of the career, and thus on the possibility of ending up in a job for which one is overeducated.

The economic intuition behind this is that while the characteristics of the Ph.D. course and of the agent have a potential impact on all three equations, and thus are always included as regressors, some variables (namely the ones affecting the likelihood to migrate, to choose a career in academia or to be in a specific kind of career) are included only in a specific equation.

4. Results

4.1 The effect of migration on overeducation

Table 5 illustrates the results achieved when equations [2] and [3] are simultaneously estimated through the *biprobit* model. Estimates calculated when considering equation [1], meanwhile, are reported in table A in the appendix but not commented here. Indeed, they are not central to the aim of this study since they were merely instrumental in the calculation of the IMR included among regressors in equation [2], with the aim of taking into account respondents' self-selection into migration.

In table 5, four specifications are presented. For each of them, results for both the selection equation (where non-academic is the dependent variable) and the outcome equation (where the dependent variable is overeducation) are reported. Coefficients calculated through the first specification (a) allow us to generally investigate the effect of Ph.D. holders' spatial mobility (within-country inter-regional migration) on overeducation. This effect is measured by the coefficient calculated for the migration dummy that is included among the regressors in equation [3]. In each of the additional

models presented in table 4, the specification considered in model (a) is augmented by one dummy that identifies a specific direction of migration. Following Iammarino and Marinelli (2015), migration from Southern Italian regions towards Northern ones is considered in model (b), where the S-CN Migration dummy appears among the covariates; model (c), meanwhile, analyses the case of migration from a region in the Centre-North towards another one in the same area through the inclusion of the CN-CN migration dummy. Finally, migration from a region in the South towards another one in the same area, which is observed by the S-S- migration dummy, is analysed in model (d).

For each of the specifications the corresponding *artrho* statistics are shown at the bottom of the table to provide information concerning the existence of a sample selection phenomenon and to assess the adequacy of the empirical approach adopted. According to the high statistical significance of such a test in all the models ($p < 0.001$), the data suggest that Ph.D. holders' self-selection into non-academic employment is an issue that has to be taken into account when analysing overeducation.

Moving to the investigation of regressors' results reported in Table 5, the first noteworthy finding is that the migration dummy reports a negative coefficient sign and a valuable coefficient size (ranging from 0.18 to 0.22), in three out of the four specifications considered where it turns out to be highly statistically significant ($p < 0.001$). According to such a finding, when taking into account the endogenous selection of Ph.D. holders into non-academic employment and the endogeneity of the migration choice, moving from one region in Italy to another in the same country eases finding a job in line with the Ph.D. title owned. In other words, this result supports the idea that spatial mobility, i.e. migration, has a negative impact on the probability of being overeducated, which is a result that extends previous findings based on the analysis of university graduates (Iammarino and Marinelli, 2015; Büchel and Van Ham, 2003; van Ham et al., 2001)⁴.

In model (c), where the migration dummy is not statistically significant, the CN-CN variable – which identifies migration among Northern Italian regions – turns out to be highly statistical significant and reports a valuable coefficient size (0.29 higher than what was found for the migration dummy) that has a negative sign. The Variance of Inflator Factor (VIF) test suggests for this model (as well as for the others) the absence of multicollinearity problems, since all the covariates' VIF is far below the threshold values of 10 and 5 suggested by the literature (Haire et al., 1995; Ringle et al., 2015).

⁴ We also run an OLS and a Probit model that did not account for any endogenous selection into migration and into the academic working sector. These models were built by using OVEREDUCATION as the dependent variable and by including MIGRATION and ACADEMY among the covariates. The results achieved through these models were qualitatively similar to those presented here

According to this finding, only those Ph.D. holders who studied in a region in the Northern part of Italy and subsequently migrate towards another region in the North gain labour matching benefits from migration. As a matter of fact, the results obtained in model (b) suggest that migration from Southern regions towards the Centre-North has a slightly statistically significant effect on overeducation, which, nevertheless, is positive, contrary to expectation. The same is found when looking at migrations from Southern regions towards other regions in the South (model d).

One might think that overeducation is less likely to occur in Northern regions where higher GDP per capita and R&D spending stimulate the demand for Ph.D. level skills. In line with such an expectation, migration towards Northern regions, independently from the region of origin, should result in lower overeducation. Nevertheless, our results confirm this hypothesis only when migration among Northern regions is taken into account.

On the one hand, this result might be explained by considering job search costs. Ph.D. holders who move across Northern regions “go shopping” for better opportunities because they face smaller job search costs. They need to cover short distances to enter other Northern regions and their travel expenses are generically low. This may explain why in the case of the Centre-North the benefit from migrating is positive: not only is there an abundant and diverse job supply, but the limited search costs can also justify a mobility which ends up with a better match between job and education (from the individual’s point of view). In the case of South-North mobility, meanwhile, the job search costs increase and Ph.D. holders are more likely to be obliged to find a job as soon as possible to cover their living/travelling expenses: this may increase the likelihood of discrepancy between education and the tasks requested in the occupation activity. A related concern is the effectiveness of placement services offered by the issuing Northern universities and/or the successful job searching channels and strategies (e.g. use of institutionalized intermediaries), which may further reduce the search costs and favour Ph.D. job matching for graduates moving throughout Northern regions.

On the other hand, this result might be explained by considering the reputation of the university issuing the Ph.D. title and its effect on job opportunities. In general, Northern Italian universities are better ranked compared to Southern ones: in the list of 180 departments rated “excellent” by the ANVUR⁵ (the Italian National Agency for the Evaluation of the University and Research), only 13% are located in the South (islands included) while 87% are in the North.⁶ The university with the

⁵ The list can be found at the following address: <http://www.miur.gov.it/dipartimenti-di-eccellenza>

⁶ A study on the distribution of these departments can be found here: <https://www.roars.it/online/dipartimenti-di-eccellenza-anvur-secreta-i-calcoli-cantone-se-ci-sei-batti-un-colpo/>

highest rating in Italy according to the QS World University Ranking⁷ is the Politecnico di Milano, which is in Lombardy, a Northern region. University rankings, by evaluating university reputations, are considered a tool for measuring the quality of academia by external stakeholders: rooted in the “massification, marketization, and globalization of higher education”, rankings can help students to compare institutions within and between countries and consumers to “see the value of their investment in higher education and hold institutions accountable for results” (Shin et al., 2011, p. 3). Over recent years, in the light of the new governance framework which is focused around selective incentives for universities (Capano et al., 2017), competition among universities has notably increased. Such a competitive system, in a country already characterized by a significant territorial divide in the allocation of human capital and quality education (Cipollone et al., 2010), has increased inequality between institutions by reshaping higher education markets on the basis of university rankings (Locke, 2011). In the case of Ph.D. holders, employers as well as intermediary agencies or research funders located in the northern part of the country, supposing that the quality of the education title is related to the positioning of the issuing university, in the presence of information asymmetries, are now more likely to select the doctoral graduates whose university is better ranked amongst others. This will imply a lower chance for Ph. D. holders coming from Southern universities to obtain a job in line with their competences.

Finally, a further outcome is that migration across Southern regions is more likely to cause a job-skills mismatch. The explanation not only has to be found in the shortage of qualified jobs in the South but also in the job search activity: according to the last *Report on the Situation of the Country* released by the National Institute of Statistics (2018),⁸ the use of informal networks (word of mouth, whistleblowing) plays an important role in the intermediation of work in Italy. This is especially true in the “Mezzogiorno” area, where the use of formal channels like job centres and private agencies is extremely low compared to the North and Centre. However, as observed in the Report, the use of informal networks does not follow “market logic or... criteria of efficiency and meritocracy, as the selection is entrusted to the fiduciary relationship and can respond to mutual interest or opportunity calculations” and may thus increase the likelihood of mismatch, as confirmed by the 2016 survey results cited in the Report.⁹ While better educated individuals are more prone to use formal job searching channels, considering that the activity of private intermediaries is proportional to the presence of job opportunities in the territory and may turn out to be scarce, it is more likely that Ph.D. holders moving across Southern regions use informal networks as a further strategy to find a job. This

⁷ <https://www.topuniversities.com/qs-world-university-rankings>

⁸ The job market section of the Report (titled “Job and networks”) can be found at the following address: <https://www.istat.it/storage/rapporto-annuale/2018/capitolo2.pdf>

⁹ See paragraph 2.3, pp. 112-115.

may cause a misalignment between education and job activities (and, probably, related concerns about job satisfaction and the valorization of human capital), which becomes the distorting effect of a supply-demand matching obtained through an unstructured channel.

4.2 Other correlates of overeducation

While the main focus of the paper is on the migration/overeducation nexus, results obtained for the other covariates might be of interest even though they are strongly in line with the existing empirical literature that has investigated overeducation among Ph.D. holders in Italy (Ermini et al., 2017a; Gaeta, 2013 and 2015). Ph.D. holders in Social Science and Humanities tend to be more overeducated than their colleagues with a Ph.D. in the PE group (which can be defined as hard sciences). Female Ph.D. holders are slightly more likely to be overeducated, which contradicts recent studies that investigate the gender gap in overeducation among Italian university graduates (De Luigi and Santangelo, 2017). Being unmarried, on the other hand, has a negative effect on over-education, probably because there is less pressure to find a job; the idea being that if an individual does not have a family yet, he or she may invest more time to find a better job.

Working in the public sector has a strong and very significant negative effect on overeducation, while being self-employed has a positive effect on the possibility of being overeducated. The first result is likely due to the legal value of the degree, which in Italy makes it impossible to discriminate between the degrees from different universities and, to some extent, between degrees (and this is especially true in the public sector). This means that Ph.D. holders have a competitive advantage in the selection for public careers compared to those without a Ph.D., even if their education is not useful for the specific job they are applying for. Thus, it is hard to state that a Ph.D. is not useful in following a career in the public sector. The second result, on the other hand, is likely to be due to a trade-off between stability and quality of the job, while the ones preferring the former end up in worse jobs, for which they are overeducated. This reasoning can be applied to explain the coefficients of the *fulltime* and *permanent contract* dummies, which are positive, suggesting a greater probability of being overeducated for people with these kinds of contracts. Indeed, greater stability can be traded in this case as well for jobs in which there is a mismatch between one's education and the tasks requested.

The self-employed dummy has a strong statistically significant positive effect in all the different specifications. Considering that the vast majority of Ph.D. holders who are self-employed come from engineering and law, (respectively 338 and 416, so 754 out of the 1,928 self-employed in our sample, i.e. 39.10% of the total) it is likely that the feelings of overeducation among these professionals comes

from the fact that their doctorates are not necessary in their specific career. In other terms, they do not feel they are using the education obtained in the tertiary cycle of studies, since the vast majority of their colleagues only have undergraduate level degrees.

Finally, the coefficients of the dummy variables on age suggest that the older the student is when he or she achieves a Ph.D., the greater the chances are of ending up in a job for which he or she is overeducated. There is apparently no effect of being an alumnus from 2010 or from 2008. This suggests a certain stability in the estimates, even in the longer term.

5. Conclusion

Does migrating allow Ph.D. holders to gain access to a job more in line with the studies they have completed? By analysing recently collected survey data from Italy that allow us to inspect respondents' within-country migration across macro-regions, this study suggests a positive answer to such a question in a specific area of the country.

Applying a statistical model that takes into account the endogeneity and self-selection of the sample, we found that migration eases job-education matching. This result extends the existing literature, which is mainly focused on university graduates, by demonstrating that spatial mobility also exerts a positive effect on job/education matching among doctoral graduates (Iammarino and Marinelli, 2015; Büchel and Van Ham, 2003; van Ham et al., 2001).

Our descriptive analysis suggests that Ph.D. holders' migration flows in Italy are mostly from Southern regions towards the Centre-North of the country, which is in line with the literature as well as anecdotal evidence. Nevertheless, our analysis suggests that only migration within the Central and Northern regions of the country actually eases job-education matching. Our interpretation is that these results may be due to the higher R&D employment opportunities which are observed in the Centre-North of Italy, combined with one or more of the following: i) lower search costs experienced by Ph.D. holders who look for a job in the same macro-area where they have studied; ii) higher rankings/reputations reported by universities in the Centre-North; iii) better non-academic placement services offered by universities in the Centre-North and differences in the use of formal job searching channels which are more likely to ensure the education-job match.¹⁰

Future studies may further investigate the reliability of these interpretations.

¹⁰ See the cited Report at page 115.

Furthermore, they might apply this analysis to different countries, trying to strengthen and generalize the results found here, or investigate a sub-sample of Italian Ph.D. holders showing specific characteristics of special interest (e.g. field of study).

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Table 1 – Migration matrix

<i>University area</i>	<i>Residence area</i>			<i>Total</i>
	<i>North</i>	<i>Centre</i>	<i>South</i>	
<i>North</i>	3,587 (89.7%)	267 (6.7%)	144 (3.6%)	3,998
<i>Centre</i>	379 (12%)	2,504 (79.6%)	263 (8.4%)	3,146
<i>South</i>	430 (12.7%)	399 (11.8%)	2,563 (75.6%)	3,392
<i>Total</i>	4,396	3,170	2,970	10,536

Source: Authors' elaboration on data from the Italian survey on employability of Philosophiae Doctor holders (ISTAT 2014).

Table 2 – Description of variables used in the empirical analysis.

Label	Description
Overeducation	Equal to 1 if overeducated.
Migration	Equal to 1 if is resident in a different region from the one In which the earned PhD.
S-S	Equal to 1 if migrated from South to South.
S-CN	Equal to 1 if migrated from South to Centre or North.
CN-CN	Equal to 1 if migrated from Centre or North to Centre or North.
ErcSH	Equal to 1 if the PhD was in the SH group, according to the ERC classification.
ErcPE	Equal to 1 if the PhD was in the PE group, according to the ERC classification.
PhDin2010	Equal to 1 if earned the PhD in 2010, to 0 if was awarded in 2008.
Sex	Equal to 1 if gender is female.
Marital Status	Equal to 1 if not married.
Age=31	Equal to 1 if earned PhD when 31 years old.
Age=32	Equal to 1 if earned PhD when 32 years old.
Age>32	Equal to 1 if earned PhD when older than 32 years.
ParentDegree	Equal to 1 if at least one of the parents has a degree.
ForCit	Equal to 1 if holds a foreign citizenship.
ForDegree	Equal to 1 if has a master's degree from a foreign university.
MigrBPhD	Equal to 1 if the PhD is from a different region from the university that awarded the master's.
Visiting	Equal to 1 if did a visiting during the PhD.
DegreeGrade>107	Equal to 1 if master's degree was higher than 107.
Scholarship	Equal to 1 if benefited from a scholarship during PhD.
Teaching	Equal to 1 if did some teaching during PhD.
InTime	Equal to 1 if finished PhD in time.
Articles	Equal to amount of articles published since the end of PhD.
Chapters	Equal to amount of chapters published since the end of PhD.
Monographies	Equal to amount of monographs published since the end of PhD.

Non Academic	Equal to 1 if not working in university.
DIndustry	Equal to 1 if the individual works in the industry sector
DService	Equal to 1 if the individual works in the services sector
DPA	Equal to 1 if works in the public sector.
PermanentContract	Equal to 1 if worker has a permanent contract.
Fulltime	Equal to 1 if worker has a full-time contract.
PIVA	Equal to 1 if works as self-employed.

Table 3 – Descriptive statistics

<i>Variable</i>	<i>N</i>	<i>Mean</i>	<i>SD</i>	<i>Min</i>	<i>Max</i>
<i>Migration</i>	13,262	0.2745862	0.446321	0	1
<i>ErcSH</i>	13,262	0.3461538	0.4757595	0	1
<i>ErcPE</i>	13,262	0.3348866	0.4719672	0	1
<i>PhDin2010</i>	13,262	0.5102935	0.4999114	0	1
<i>Sex</i>	13,262	0.539157	0.4984817	0	1
<i>Marital Status</i>	13,262	0.4922799	0.4999578	0	1
<i>Age=31</i>	13,262	0.2735429	0.4457926	0	1
<i>Age=32</i>	13,262	0.4764919	0.4994644	0	1
<i>Age>32</i>	13,262	0.2499652	0.4330077	0	1
<i>ParentsDegree</i>	13,262	0.3725831	0.4835093	0	1
<i>ForCit</i>	13,262	0.01238	0.1105785	0	1
<i>MigrBPhD</i>	13,262	0.2118615	0.4086447	0	1
<i>ForDegree</i>	13,262	0.0120323	0.1090336	0	1
<i>Visiting</i>	13,262	0.3602031	0.4800759	0	1
<i>InTime</i>	13,262	0.8421895	0.3645759	0	1
<i>Articles</i>	13,262	6.652177	9.245478	0	50
<i>Chapters</i>	13,262	1.219572	2.495984	0	14
<i>Monographies</i>	13,262	0.3238976	0.9317911	0	10
<i>Scholarship</i>	13,262	0.6966198	0.459734	0	1
<i>Teaching</i>	13,262	0.750313	0.4328469	0	1
<i>DegreeGrade>107</i>	13,262	0.7227709	0.4476461	0	1
<i>DIndustry</i>	13,262	0.0752539	0.2638097	0	1
<i>DServices</i>	13,262	0.8264014	0.3787771	0	1
<i>DPA</i>	13,262	0.5577966	0.4966656	0	1
<i>Fulltime</i>	13,262	0.6176798	0.4859711	0	1
<i>Permanent</i>	13,262	0.3476144	0.4762294	0	1
<i>Contract</i>	13,262	0.3476144	0.4762294	0	1
<i>PIVA</i>	13,262	0.1340938	0.3407649	0	1

Table 4 – Dependent variable (y) and covariates (x) used in each step of the analysis.

Variable		Step 3	Step 2	Step 1
		Overeducation equation	Non Academic equation	Migration equation
Variables the study is focused on	Overeducation	y		
	Non Academic		y	
	Migration	x		y
	S-S	x		
	S-CN	x		
Sample stratification variables	CN-S	x		
	ErcSH	x	x	x
	ErcPE	x	x	x
Socio-demographics	PhDin2010	x	x	x
	Sex	x	x	x
	Marital Status	x	x	x
	Age=31	x	x	x
	Age=32	x	x	x
	Age>32	x	x	x
	ParentDegree			x
Migration before Ph.D. completion	ForCit			x
	MigrBPhD			x
	ForDegree			x
	Visiting			x
Ph.D.-related variables	InTime		x	
	Articles		x	
	Chapter		x	
	Monographies		x	
	Scholarship		x	
	Teaching		x	
	DegreeGrade>107		x	
Job-related variables	DIndustry	x		
	DService	x		
	DPA	x		
	Fulltime	x		
	PermanentContract	x		
	PIVA	x		

Table 5 – Results obtained through the estimation of the overeducation (outcome) equation and of the non-academic (selection) equation.

	(a)	(b)	(c)	(d)
Outcome equation. Dependent variable: overeducation				
Migration	-0.184*** (-4.38)	-0.217*** (-4.63)	0.0759 (0.83)	-0.210*** (-4.90)
S-CN Migration		0.133* (1.72)		
CN-CN Migration			-0.299*** (-3.14)	
S-S Migration				0.380** (2.52)
ErcSH	0.539*** (9.85)	0.540*** (9.86)	0.542*** (9.88)	0.543*** (9.90)
ErcPE	-0.104** (-2.32)	-0.105** (-2.33)	-0.101** (-2.25)	-0.102** (-2.27)
Sex	0.0847** (2.12)	0.0859** (2.15)	0.0841** (2.11)	0.0845** (2.11)
DPA	-0.367*** (-8.43)	-0.372*** (-8.50)	-0.369*** (-8.47)	-0.369*** (-8.45)
PIVA	1.062*** (11.50)	1.066*** (11.53)	1.059*** (11.44)	1.061*** (11.48)
Marital Status	-0.0995** (-2.54)	-0.101** (-2.56)	-0.0964** (-2.45)	-0.0970** (-2.47)
Age=31	0.195*** (4.39)	0.196*** (4.41)	0.190*** (4.29)	0.194*** (4.37)
Age=32	0.565*** (9.11)	0.569*** (9.16)	0.560*** (9.02)	0.562*** (9.05)
DIndustry	0.0983 (0.76)	0.0956 (0.74)	0.106 (0.82)	0.102 (0.79)
DServices	-0.0331 (-0.31)	-0.0350 (-0.32)	-0.0269 (-0.25)	-0.0288 (-0.27)
PhDin2010	0.0696* (1.79)	0.0698* (1.79)	0.0703* (1.81)	0.0701* (1.80)
Fulltime	0.575*** (13.16)	0.572*** (13.08)	0.579*** (13.24)	0.580*** (13.24)
Permanent Contract	0.477*** (10.17)	0.479*** (10.20)	0.479*** (10.20)	0.477*** (10.15)
DegreeGrade>107	0.135*** (3.07)	0.133*** (3.02)	0.133*** (3.03)	0.133*** (3.03)
Constant	0.669*** (5.20)	0.674*** (5.23)	0.662*** (5.15)	0.661*** (5.13)
Selection Equation. Dependent variable: non-academic				
IMR Eq Migration	2.076*** (7.46)	2.074*** (7.46)	2.072*** (7.45)	2.073*** (7.46)
Migration	-3.209*** (-6.90)	-3.206*** (-6.89)	-3.203*** (-6.89)	-3.204*** (-6.89)
Sex	-0.0806*** (-3.09)	-0.0806*** (-3.09)	-0.0804*** (-3.08)	-0.0806*** (-3.09)
Marital Status	0.0309 (1.02)	0.0308 (1.02)	0.0307 (1.02)	0.0306 (1.01)
Age=31	0.182*** (6.25)	0.182*** (6.25)	0.182*** (6.26)	0.182*** (6.25)
Age=32	0.288*** (7.84)	0.287*** (7.83)	0.288*** (7.85)	0.288*** (7.84)
PhD2010	-0.172*** (-6.53)	-0.172*** (-6.53)	-0.172*** (-6.54)	-0.172*** (-6.54)
InTime	-0.0381 (-1.08)	-0.0383 (-1.09)	-0.0384 (-1.09)	-0.0382 (-1.08)
Articles	-0.0289*** (-1.08)	-0.0289*** (-1.09)	-0.0289*** (-1.09)	-0.0289*** (-1.08)

	(-22.43)	(-22.41)	(-22.42)	(-22.43)
Chapters	-0.0741***	-0.0741***	-0.0741***	-0.0740***
	(-14.69)	(-14.69)	(-14.70)	(-14.68)
Monographies	-0.0783***	-0.0783***	-0.0783***	-0.0783***
	(-6.12)	(-6.11)	(-6.12)	(-6.11)
ERCSh	0.333***	0.333***	0.332***	0.332***
	(5.16)	(5.16)	(5.15)	(5.15)
ERCPE	-0.0589*	-0.0586*	-0.0591*	-0.0589*
	(-1.90)	(-1.89)	(-1.91)	(-1.90)
Scholarship	-0.318***	-0.318***	-0.318***	-0.318***
	(-11.19)	(-11.19)	(-11.19)	(-11.20)
Teaching	-0.154***	-0.154***	-0.154***	-0.154***
	(-5.26)	(-5.28)	(-5.27)	(-5.27)
DegreeGrade>107	0.0158	0.0158	0.0155	0.0157
	(0.56)	(0.56)	(0.55)	(0.56)
Constant	2.024***	2.023***	2.023***	2.023***
	(15.89)	(15.89)	(15.89)	(15.89)
athrho	-0.912***	-0.905***	-0.917***	-0.906***
	(-7.61)	(-7.59)	(-7.63)	(-7.61)
Observations	13262	13262	13262	13262

Note: the table reports coefficients and t statistics (in parentheses) * p < 0.1, ** p < 0.05, *** p < 0.01.

APPENDIX

Table A – Results obtained through the estimation of the migration equation.

Dependent variable: migration	(1.1) Migrated post-PhD
ForCit	-0.337* (-1.89)
PhDin2010	-0.0641*** (-2.83)
DegreeGrade<104	0.00489 (0.14)
DegreeGrade<107	0.00101 (0.03)
Age=32	-0.00220 (-0.08)
Age=33	0.000573 (0.02)
MigrBPhD	0.0501 (0.18)
ParentDegree	0.0703*** (3.01)
Sex	-0.0420* (-1.81)
ERC SH	0.336*** (12.01)
ERC PE	-0.00835 (-0.28)
Visiting	0.113*** (4.75)
ForDegree	0.136 (0.60)
Marital Status	0.116*** (5.06)
Constant	-0.839*** (-2.97)
Observations	14378

Note: the table reports coefficients and t statistics (in parentheses) * p < 0.1, ** p < 0.05, *** p < 0.01.