Overeducation and overskilling
in the early careers of Ph.D. graduates:
Does international migration reduce labor market mismatch?

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Abstract

This paper examines the effect of international mobility on the education-job mismatch of Ph.D. graduates while controlling for self-selection into cross-border mobility. Skilled migration flows have risen significantly over the past decades, with a sizable share of migrants being overeducated. Yet, in this broad context, the empirical literature has so far largely overlooked the specific case of doctorate recipients, as well as the extent to which their spatial mobility to international countries represents a strategy that reduces the risk of being mismatched. The empirical analysis uses individual-level data collected by ISTAT on the population of Italian Ph.D. recipients and shows that migration reduces considerably the risk of overeducation and overskilling. Results are robust to different methodologies and subsamples.

JEL codes:
Keywords: overeducation; overskilling; skilled migration; international migration; PhD degree.

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1. Introduction

The role of doctoral recipients in promoting research and driving innovation is stressed in the literature (Stuen et al. 2012). In particular, the European Union policy agenda emphasizes the role of doctoral recipients since PhD education and training can help achieve the Lisbon goal of developing a competitive-knowledge based economy. However, in order to achieve these goals it is imperative that the doctoral recipients accept jobs that exploit their skills and training. A doctoral recipient would typically search for a job matching his/her education in their geographical area. When they cannot achieve this they could either accept a job requiring less education or skills; remain unemployed or outside the labor force, or widen the job search area (Büchel & van Ham 2003). If a doctoral recipient accepts a job that requires less education or skills than what they have acquired then they are mismatched for the job thus resulting in overeducation or overskilling. This labor market mismatch could be potentially costly both for the PhD recipient and society due to lower levels of productivity, lower job satisfaction and the inefficient use of investment made in education. (McGuinness 2006). Consequently, this has led to a growing literature documenting the incidence of labor market mismatch in the early career of young workers (Dolton & Vignoles 2000).

Paralleling the literature on labor market mismatch is the fact that international skilled migration flows have risen significantly over the past few decades. For example, amongst OECD countries, highly educated foreigners exceed 31 million and comprise 45 percent of the increase in the foreign-born population (Arslan et al. 2015). Countries attract these highly skilled immigrants in order to increase technology development, innovation and economic performance, which is often done by introducing quality-selective immigration policies, such as tax benefits and simplified immigration measures, to attract talent from all over the world (Beine et al. 2008). Bosetti et al. (2015) provide evidence that skilled labor matters for innovation in that skilled migrants employed in highly skilled jobs leads to higher levels of innovation in a panel of 20 European countries between 1995 and 2008.

Previous studies have documented that the probability of finding jobs that match both education and skills increases when there is higher labor mobility (Hensen et al. 2009). Thus the objective of this paper is to investigate the role that spatial mobility, specifically the ability of labor to move *abroad*, has on the education-job mismatch and skill-job mismatch of PhD graduates while controlling for self-selection into cross-border mobility. While the number of PhD students graduating from universities in OECD countries have increased by 38 percent over 2000-2009 (Auriol et al. 2013), opportunities for academic employment have declined over time (Larson et al. 2014). International migration of PhD recipients can thus contribute towards reducing overeducation or overskilling In fact, the literature indicates that limiting the geographical scope of a graduates' job search is one of the explanations for the existence of education–job mismatch (Iammarino & Marinelli 2015).

This study contributes to the existing literature on job mismatch in several ways. First, while higher education graduates have received much attention in the empirical literature (Carroll & Tani 2013; Venhorst & Cörvers 2017; Barone & Ortiz 2010; McGuinness & Byrne 2015), scholars have so far largely overlooked the specific case of doctorate recipients, as well as the extent to which their spatial mobility represents a strategy that reduces the risk of being overeducated or overskilled. Using data from the Professional Integration Survey of PhDs administered by the Italian National Institute of Statistics (ISTAT) on Italian PhD graduates, we focus on this issue by investigating whether international migration of PhD degree holders in Italy reduces job mismatch. Moreover, the Italian labor market for PhD recipients provides us with a good case to understand the role of spatial mobility on overeducation and overskilling. While the number of PhD degrees awarded by Italian universities has increased from 4,000 in 2000 to over 12,000 in 2008 (Italian National Institute of Statistics, 2009) there are fewer permanent positions in universities and public research centers available (Ballarino & Colombo 2010). This has led to the literature examining the impact of spatial mobility on mismatch in the context of mobility *within* Italy. However, to the best of our knowledge, there has been no earlier study on the spatial mobility of Italian PhD recipients at the *international* level. For example, Croce and Ghignoni (2014) show that migration between Italian provinces reduces overeducation among university graduates, and Iammarino and Marinelli (2015) find that migration from the Southern regions to the Northern regions of Italy reduces overeducation. On the other hand, Devillanova (2012) finds that migration displays no effect or a positive effect on overeducation, after controlling for the characteristics of the job. This study therefore investigates this issue both in the context of understanding whether the spatial mobility of Italian PhD recipients to foreign countries leads to a lower probability of mismatch as well as in the context of the transfer of high-skilled human capital from Italy to foreign countries. PhD recipients by moving to foreign countries to find jobs that match their education and/or skills level allows them an added geographical locational opportunity that could potentially allow them to exploit the skills acquired during the doctoral program more completely.

Second, we contribute to the strand of literature debating the measurement of the employer–employee mismatch. As clarified in Allen et al. (2001), formal educational mismatches (actual versus required level of education to get a job) do not necessarily overlap with actual skill mismatch (acquired versus required level of skills). Due to the increasing participation in higher education programs, job entry requirements are no longer able to proxy the job skill content (Mavromaras & McGuinness 2012). Mavromaras et al. (2010) and McGuinness and Byrne (2015) argue that overskilling is a better measure for employer-employee mismatch. In this paper, we use a new measure of overskilling where we first rely on standard measures based on workers' self-assessment and then exploit information on the R&D content of the job in order to capture the mismatch between the academic research training received before graduation and the actual job duties. Thus this study also contributes to an emerging literature focused on the understanding of the factors affecting the ability of PhD recipients to pursue a research-oriented career.

Third, this study of the mobility of PhD students to international countries is important from the host country perspective since this group of tertiary education embodies high-skill labor and knowledge that could lead to higher innovative activities and knowledge creation in the host country (Bosetti et al. 2015; Chellaraj et al. 2008). These results thus have some important policy insight for countries that are open to receiving international students. Finally, the empirical results on the postdoctoral rates of R&D employment could provide insight into plausible indicators of the success of PhD-granting institutions.

The rest of the paper is organized as follows. Section 2 provides some background information on the literature. Section 3 describes our data. The methods used in this study are described in section 4 and section 5 discusses the empirical results. Section 6 concludes.

2. Overeducation, Overskilling and International Mobility of PhD Degree Holders

While overeducation is explained through several theories we focus on the human capital theory. This explains overeducation as an investment in various forms of human capital such as formal school, work experience and skills acquired through on-the-job training. Thus, a PhD recipient when entering the labor market may take a job that requires lesser skills than their formal degree with the goal of gaining experience for future job mobility; in this case overeducation is presumed to be a transitory phenomenon (Chiswick & Miller 2009).

When considering the role of spatial mobility on overeducation in the labor market the literature has considered two distinct types of migration: internal migration and international migration. The basic intuition is that jobseekers have a higher probability of finding suitable jobs if their geographic search area is enlarged, so both internal migration, as seen in inter-regional movements within a country, and cross-country migration can lead to better job matches.

The rationale for international mobility in the case of PhD recipients varies. In a survey of OECD countries, 43.9 percent of PhD holders who planned to go abroad stated it was for academic factors, 30.9 percent said it was due to other job related or economic factors and 15 percent said it was for family or personal reasons. Differences related to the opportunities after the research training received during the PhD program can also play a role in international movements such as differences in research funding between the home location and foreign location or exploiting an academic network abroad to increase the probability to obtain a job in their field of specialization (Di Cintio & Grassi 2016).

In general, there are very few studies that study the international spatial movements of PhD recipients and, typically, they tend to focus on international PhD students in the United States. This stems from the fact that there were about 610,000 foreign-born doctorate holders in the United States in 2005-2009 representing 27 percent of the total population of doctorate holders in the U.S. (Auriol et al. 2013). Grogger and Hanson (2015) investigated the location choices of foreign-born science and engineering students receiving a PhD from US universities and concluded that individuals in countries with the leading research organizations in the world show a lesser need to move abroad. Di Cintio and Grassi (2016) examined two cohorts of Italian doctoral students and finds that their international mobility is associated with higher wages and they conclude that for highly educated individuals spatial mobility increases the chances to capitalize the investment in education.

3. Data and Variable Description

The data for the empirical analysis are drawn from the Professional Integration Survey of PhDs (*Indagine sull'inserimento professionale dei dottori di ricerca*) administered by the Italian National Institute of Statistics (ISTAT). Currently, there are two waves of the survey and each one contains information on two cohorts of doctorates who received a degree from an Italian university three and five years before the interview, respectively. Specifically, the first survey was conducted between December 2009 and February 2010 and collected information on about 13,000 PhD recipients, with an overall response rate of around 70 percent. The second wave of the survey was conducted between February and July 2014 collecting more than 16,000 compiled questionnaires, which correspond to a response rate of slightly more than 70 percent. The survey questionnaire has five sections and provides extensive information on individual curricula, characteristics of the PhD program, job characteristics, retrospective patterns of spatial mobility and current as well as origin family status.

The analyses presented in this paper target all PhDs who are in paid employment at the time of the survey. At first glance, this choice could be criticized as it potentially introduces some form of selectivity in our sample. Nevertheless, 92.8 % of PhDs report to have a job and, among those without a job, almost 22 % report they are waiting either to go back to their previous job or to start a new job or a paid training program. For this reason, we believe that the bias associated to selection into employment plays a little role in our study and we focus the analysis on individuals holding a job. After eliminating observations for which independent and/or control variables are missing, the final sample is made up of 13359 for the analysis of overeducation and 21169 individuals for the analysis of overskilling.

An advantage of our dataset is that it contains enough information to study the impact of migration on both overeducation and overskilling. In particular, we use three survey questions to classify a PhD recipient as mismatched. First, PhD holders were asked to indicate if the degree was a formal requirement in order *to obtain the job*, and the answer categories were: (i) explicitly requested; (ii) no but it has been useful; and (iii) the PhD degree was neither requested nor useful to get the job. While individuals can unambiguously declare if the PhD was a formal requirement to get the job, the usefulness of the PhD degree, i.e. the second possible answer, is more a personal opinion. Thus, we have used the question to build two distinct dummy variables both capturing the status of overeducation. The first one has been labeled *PhD_requested* and takes the value of one when respondents declare that the degree was neither requested nor useful to get the job and is equal to zero when respondents state that the degree was explicitly requested. Thus the variable does not consider individuals who report that the degree was *useful* to get the job.[1] The second variable has been labeled *PhD_requested/useful* and takes the value of one as before, but is equal to zero when respondents state that the degree was either requested or useful. According to this latter variable, 26 percent of PhDs are classified as overeducated. This is in line with what is reported in the *EU* survey on European skills and jobs, according to which

[1] While we are aware aware that this choice inflates the number of PhDs considered as overeducated (51.89 percent), the variable does not suffer from the bias related to the individual perception of the usefulness of the degree.

almost 24.4 percent of EU tertiary graduates state that their degree was needed exclusively for recruitment purposes.[2]

A second way to measure mismatch exploits the fact that PhDs were asked whether having a PhD was actually needed *to carry out the job*, and the answer categories were yes or not. This is a standard self-assessment measure for overskilling that we use to build the variable *PhD_needed*.[3]

Finally, we introduce a novel measure for mismatch by taking advantage of the fact that PhDs were asked to report if they carry out R&D activities in their current job; the possible answers were yes fully, yes partly, not at all. Also, in this case, we built two alternative indicators for labor market mismatch. One indicator does not consider individuals who respond that they partly do R&D activities (*Full_R&D_job*), and the second indicator considers as a single category those who report they are engaged in R&D activities in their job either fully or partly (*Full/partly_R&D_job*). The intuition behind this is that PhDs are specifically trained to do research, irrespective of the field of study, and if they do not carry out research in their job, they have acquired more skills than their current job requires. In this sense, our measure of overskilling allows us to check whether or not PhDs utilizes the doctoral education in their current jobs. There is a growing skepticism in the literature about the use of overeducation as a measure of market mismatch (Dolton & Vignoles 2000; McGuinness & Bennett 2007), while measures related to the overskilling of workers are considered more reliable and closely related to the acquired human capital. Yet, many studies construct their measures of overskilling from subjective evaluations of interviewed. For instance, the Household, Income and Labour Dynamics in Australia (HILDA) survey ask individuals about the extent to which they are able to use their abilities and previously acquired skills on the job (Mavromaras et al. 2010). Similarly, Allen and De Weert (2007) use cross-country survey data where respondents had to report the extent to which they used the knowledge and skills they had acquired in the course of their studies. In the present study, we take it a step further as we are also able to compare a self-assessed measure for overskilling with another measure that should suffer less from subjective bias.

To assess the extent to which the same individuals are simultaneously mismatched under each measure, in table 2 we cross-tabulate the following variables: *PhD_requested/useful*, *PhD_needed*, *Full/partly_R&D_job*. We find that 24.4 percent overeducated PhDs are also overskilled according to our subjective measure while only 15.2 percent are overskilled in

[2] See McGuinness et al. (2017).
[3] The dummy takes on the value of one to indicate overskilling.

terms of R&D content of the job. These numbers closely resembles what has been documented by Allen and var den Velden (2001) in a study on Dutch graduates. The authors report that a large fraction of those who stated they were in jobs not tightly related to their level and/or field of study, nonetheless stated they were using their knowledge and skills in their work.

More importantly, only 27.68 percent of PhD graduates simultaneously report they are overskilled according to both measures of overskilling. From one viewpoint, these unconditional figures emphasize the view that alternative measures of mismatch are likely to be very different in nature (McGuinness & Byrne 2015; Mavromaras et al. 2010), thus validating our choice of conducting alternative analysis with respect to the migration status. From another viewpoint, the same figures underline the less explored issue related to subjective versus objective measures of overskilling.

In the present study, we define migrants all the PhD recipients who hold a job in a foreign country. From the inspection of table 1, we see that around 8% of doctorates opt to be mobile. Among them, around 10% are overeducated, 30% are overskilled according to our self-assessment measure for overskilling, but only 13% are overskilled in terms of R&D content of the job.

The empirical analysis includes a rich set of explanatory variables. We control for gender, age at PhD, civil status, parents' education, timely completion of the PhD, PhD scholarship and an indicator for full time job. We also add dummies to control for cohort effects, field of study, modes of access to the job, economic sector and province fixed effects. Province fixed effects are particularly relevant as in the majority of Italian provinces there is only one university. [4] Table 1 lists the main control variables and reports summary statistics for the whole sample as well as summary statistics broken down by migrant status. Interestingly, the sub-populations of migrants and non-migrants differ substantially along several dimensions. The share of mobile females is 37.4%, even if, overall, females are 50.3% in the overall sample, suggesting that, on average, males tend to be far more mobile. Those who move show a tendency to be younger and non-married, in full time jobs and with more educated parents. The table also shows that students graduating in the fields of Industrial and Information Engineering, Economics and Statistics are more likely to move abroad.

[4] Here we anticipate the fact that since the empirical strategy involves a two-step procedure, not all the variables enter both equations. The reader will easily become familiar with our choice of regressors for each equation in the following of the paper.

4. Empirical Design

We start by considering the following binary choice model:

$$Mismatch_i = I(X_i'\beta_1 + Mig_i\gamma + \varepsilon_{i1} \geq 0), \qquad (1)$$

where *Mismatch* is the binary response for overeducation/overskilling, X is a vector of observed regressors, β and γ are coefficients, Mig is the dichotomous indicator of international mobility and ε is the error component with zero mean. If the condition inside brackets is met, then the indicator function *I* returns the value one (and zero otherwise). As migrants are likely to differ from non-migrants in unobservables which are likely to be correlated with the probability of being mismatched, a probit model would deliver estimates reflecting also the impact of confounding factors such as innate ability, ambition and risk aversion. For example, if migration is positively related to ambition (or ability), migration and mismatch might be negatively correlated even in the absence of a true causal relationship. This is an endogeneity problem threatening the identification of the impact of international mobility on mismatch. To tackle this issue, we specifically model the migration choice as:

$$Mig_i = I(X_i'\beta_2 + Z_i'\delta + \varepsilon_{i2} \geq 0), \qquad (2)$$

where we include a vector of instruments, Z. We select three estimation methods as possible candidates to address the above situation: (i) the bivariate probit model; (ii) the 2-stage residual inclusion (2SRI) model; and (iii) Lewbel's (2000) special regressor model. In what follows, we briefly outline each of these models.

In our particular setting, the bivariate probit model corresponds to the joint estimation of the probability of being mismatched and the probability of being a migrant. Estimation can be done by maximum likelihood, which requires the assumption of joint normality of the error terms ε_1 and ε_2, conditional upon Z. Moreover, the joint dependence of the error terms is fully characterized by a scalar parameter, ρ, which is the correlation coefficient. If equation (2) is correctly specified and the assumption of the joint normality of the error terms holds, maximum likelihood provides consistent estimates of the parameter of interest in equation (1). The identification assumptions for the bivariate probit model to produce consistent estimates are often considered too restrictive in applied works. To this end, we supplement the analysis with two other estimation methods that are especially suited for nonlinear second-stage regressions and, at the same time, relax the full parametric assumption (Blundell & Powell 2004).

Following Terza et al. (2008) we implement the 2-stage residual inclusion method which has been shown to be also appropriate in case of rare outcomes and/or rare exposure, as it is in our case. While this methodology is largely employed in health econometric research (Cheng et al. 2014; Basu & Coe 2017; Terza et al. 2008), few authors have fruitfully used it in the migration research. Specifically, the 2SRI method consists of a two-step protocol in which the first-stage equation gauges the propensity to migrate by means of a probit model that includes both exogenous variables and instrumental variables. The estimated coefficients are then exploited to compute the generalized residuals[5] (Gourieroux et al. 1987):

$$\tilde{\epsilon}_{1i}(\hat{\beta}, \hat{\alpha}) = \frac{\phi(X_i'\hat{\beta}_1 + Z_i'\hat{\delta})}{\Phi(X_i'\hat{\beta}_1 + Z_i'\hat{\delta})[1-\Phi(X_i'\hat{\beta}_1 + Z_i'\hat{\delta})]}\left[Mig_i - \Phi\left(X_i'\hat{\beta}_1 + Z_i'\hat{\delta}\right)\right],$$

where $\Phi(\cdot)$ is the cumulative density function of the standard normal distribution and $\phi(\cdot)$ is the probability density function. Generalized residuals are then included as an additional regressor in the second-stage equation along with the *observed* mismatch indicator. The generalized residuals are meant to capture the unobserved structure between the endogenous regressor and the dependent variable in the second-stage regression. In this way, the coefficient of the migration variable in the second-stage is expected to deliver the causal impact of migration upon the probability of being mismatched.

Another empirical approach, which to the best of our knowledge has not yet been used in the overeducation/overskilling literature, is Lewbel's (2000) special regressor method. As suggested by Dong and Lewbel (2015), this method has several advantages over alternative approaches used in the applied economic literature. Specifically, when used with discrete endogenous regressors, the special regressor method is less sensitive to misspecification of the first-stage equation, and is robust to unknown forms of heteroskedasticity. Moreover, the special regressor approach does not require the restrictions on the distribution of model errors to be parametrically specified. Consistency of the estimated coefficients is achieved as long as a "special regressor" V satisfies a given set of properties. In detail, V must be continuously distributed and conditionally independent of the model error, must appear additively to the error term in the equation of interest, must be conditionally positively correlated to the outcome and must have a large support.

Formally, equation (1) can be rewritten as:

$$Mismatch_i = I(X_i'\beta_1 + Mig_i\gamma + V + \varepsilon_{i1} \geq 0).$$

[5] The use of generalized residuals in place of of raw residuals attempts to stabilize the variance.

Provided the exclusion restrictions in equation (2) satisfy standard requirements for their validity and the special regressor meets the above mentioned conditions, estimation can be done as follows. First, V must be de-meaned if it is not already zero mean. Second, from an OLS regression of V on X and Z one has to recover the residuals $\hat{u}$ as the difference between the observed and predicted V. Residuals are then used to compute for each individual the Kernel density estimate $\hat{f}(\hat{u})$ which are in turn employed to construct the index $\hat{T}_i = \frac{Mismatch_i - I(V_i \geq 0)}{\hat{f}_i}$. The last step is to apply 2SLS regression of $\hat{T}_i$ on X and Z.[6]

4.1 Instrumental variables

In the methodologies adopted in this study, endogeneity is tackled with the use of instrumental variables which are excluded from the overeducation equation (1). In detail, we use five instruments and we assess their validity by means of statistical testing.

In line with previous empirical research on the determinants of graduate migration, the decision to migrate critically depends on expected wages in destination countries. Following Ciriaci (2014), we construct a destination-to-origin wage ratio based on the net monthly wages reported in the survey and the weights constructed by ISTAT.[7] Specifically, we compute the origin average wages at the NUTS 3 level (i.e. at the province level) and the destination average wages for the following destinations: France, Germany, UK, Spain, USA, other EU countries, and rest of the world. We match the resulting ratio to each individual in the sample according to the province in which the PhD attended a university and the residence at the time of the survey.

Following Croce and Ghignoni (2014), we select measures of local labour market conditions related to the area where PhDs completed their degree. In detail, we use the number of new firms, the total number of firms, the number of patents and the youth unemployment rate, all at the province level. These variables are likely to be correlated to the choice of migration, but they are also required to be unrelated to the job-match indicator in the main equation. To test whether this requirement holds for the overall set of instruments, we compute the Hansen J statistics, the weak identification test, the underidentification test and the weak-instrument-robust inference test from simultaneous two-stage GMM IV system

[6] For a more technical discussion, see Dong and Lewbel (2015) and Lewbel et al. (2012).
[7] External data sources of skilled labor wages are not available.

estimation. Table 3 reports the results for these tests and shows that the selected IVs are correctly excluded from the outcome equation while identifying the migration propensity.

4.2 Special regressor

In order to fit the special regressor model, we need a special regressor V satisfying the assumptions as defined earlier. We chose the weekly working hours to build the special regressor. The advantages of this variable are that it has a large support and can be assumed to be unrelated to the migration decision. The special regressor should also satisfy the condition such that $E(D \mid \mathbf{X}, V)$ increases with V. Since the probability of being overeducated decreases with an increase in the amount of working hours, we consider the opposite of the number of weekly working hours. Then, to increase thickness in the tails of the distribution, we take the square of the number of working hours. We finally normalize V such that it is of mean zero. Figure 1 reports the fitted kernel-weighted local polynomial regression of each of our meauseres of mismatch on V, providing evidence for an increasing relationship between them.

5. Estimation Results

Table 4a presents the results of the bivariate probit models estimated for the first three measures of mismatch, namely *PhD_requested*, *PhD_requested/useful* and *PhD needed*. The results for the remaining measures of mismatch related to R&D activities are in table 4b. In all models, and for both equations, we control for gender, age, timely completion of the degree, PhD scholarship, 14 fields of study, parents' education and cohort dummies. The survey does not disclose information on the granting institution, but it delivers information on the province in which the PhD attended a university. With few exceptions, there is usually one university per province. Thus, we include province fixed-effects in the regressions to capture differences related to the quality of the institutions attended. In the overeducation and overskilling equations, we also control for the channel used to get the job, if the job is full time, and include sector fixed effects.

Before turning our attention to the discussion of the estimation results for the impact of international mobility, we briefly summarize the effects of our control variables both in the migration and the selection equations. First of all, there are strong gender differences. While in the migration literature the majority of studies report lower migration rates for women, there is no clear evidence of gender differences in terms of overeducation/overskilling (Carroll & Tani 2013; Frenette 2004; Mavromaras & McGuinness 2012). Here, we find that females tend to migrate less (around 18 – 20 percent) and to be at higher risk of mismatch (8-9 percent). Younger individuals are more mobile and, at the same time, they have a lower probability of being overeducated and overskilled. While father's education is associated with a higher probability to migrate, mother's education is negatively associated with overskilling when measured in relation to R&D. Timely completion of the degree reduces the probability to migrate and that of overeducation. It also significantly reduces the chances of the subjective measure of overskilling (*Phd_needed*). Unexpectedly, we do not find clear cut evidence in favor of a differentiation by fields of study, even though previous research has shown that there are differences across fields of study in the likelihood of being mismatched (Ortiz & Kucel 2008). This result is challenging to explain, especially when we consider that different fields may be associated with different levels of human capital investments and different methods of research. However, we find that alternative channels to obtain the job have specific effects on the chances to be overeducated/overskilled. Compared to the baseline category of getting the job in a public competition, it is statistically less likely to observe mismatches if individuals benefit from professor referrals. This result reinforces the idea that the formal Italian recruitment system is not as efficient as it should be in providing information on workers and job characteristics to improve matches between employers and employees.

In deciding the methodologies to adopt, one of our main concerns was that mobility may be endogenous, specifically that, after controlling for observed characteristics, there might be residual variation in unobserved individual traits that affect both the probability to migrate and the probability to take a mismatched job after graduation. According to McGuinness and Byrne (2015), the existing literature linking mismatch with migrant status has largely ignored issues of selectivity. Interestingly enough, the estimated coefficients of the correlation between error terms are never significant across our models. Even when we employ two-stage IV estimations, we find no evidence in favor of endogeneity tests. To a certain extent, one possibility is that selectivity is fully accounted for through our observable variables. Moreover, our sample comprises top-educated individuals only which can be considered as a high homogenous group. For instance, McGuinness and Sloane (2011) argue that graduate cohort data are less sensible to unobserved heterogeneity bias due to the fact that "respondents have uniform levels of education and labour market experience". Nonetheless, we decided not to ignore the possibility that there are still unobservable individual traits that simultaneously affect both migration and mismatch. Thus, in the following analyses we keep using an IV strategy, even if endogeneity appears to be a negligible problem.

We now turn the attention to the impact of spatial mobility on our measures of labor market mismatch. In particular, we focus on marginal effects for the bivariate probit model reported in the first row of table 5. A clear pattern emerges from our analysis. Spatial mobility is found to reduce the probability of mismatch, as the estimated coefficients of the mobility indicators are negative and always significant at conventional levels. Moreover, the magnitudes of the effects appear to be non-negligible. Our estimates indicate that if a random individual from the population of PhDs chooses to migrate, he/she would face a 15.8 percent lower probability of getting a job for which the degree was formally required or at least useful at the hiring stage, a 20% lower probability to be overskilled and a 11.7% lower probability of being in a non-research job. These pieces of evidence broadly confirm what already found in the literature focusing on the role of spatial mobility in reducing the education-job mismatch of high-skill individuals. Büchel and Van Ham (2003) observe that most individuals only look for jobs on the regional labor market, but those who decide to widen their search area experience a decrease in the odds of overeducation.

Another implication of our results is that PhD recipients enlarging their job-search area are able to transfer abroad, at least partially, their human capital. In a study on adult native born and foreign born men in the US, Chiswick and Miller (2009) find that less-than-perfect transferability of human capital is responsible for higher rates of overeducation among immigrants, but that overeducation declines with longer duration in the host country. In this perspective, an interesting development of the present paper would be analyzing the performance of migrant PhDs within the host country.

A further look at the estimated marginal effects in table 5 suggests that there are sizeable differences in the effects of migration on overskilling when we move from a self-assessment measure (20%) to our objective measure (11.7%). First, this result challenges the appropriateness of the use of measures for overskilling based on a subjective evaluation. Second, the result highlights a tendency of the Italian economy of being unable to employ all the potential scientific workforce trained in domestic institutions.

The second and third rows in table 5 report the results obtained from alternative estimation techniques. We see that while the results from the 2SRI model are very close to the ones obtained in the bivariate probit model, the special regressor method delivers lower predicted probabilities.

6. Sensitivity checks and robustness

Up to now, estimates have been conducted on the whole sample of PhD recipients. However, the sample includes four cohorts of graduates where the two more recent cohorts graduated during the financial crises. Moved by the concern that our estimates may be sensitive to aggregate characteristics ignored so far, we hereby present estimates for each cohort separately. Results are shown in table 6.

The results broadly confirm the beneficial effect of migration, even if we lose significance for some coefficients estimated through the special regressor method. Nevertheless, this exercise makes us confident that we are actually capturing the relevant scale of the phenomenon under scrutiny as the magnitude of the coefficients does not exhibit sensible jumps or sign reversals. Estimates also suggest a slight tendency to estimate smaller coefficients for the two more recent cohorts. This is probably related to the effects of the financial crisis on labor markets that may have caused less adequate employment opportunities for PhD recipients.

Another concern is related to the inclusion in the sample of PhD graduates from all disciplines. To this end we select STEM graduates and rerun our set of estimates on this subsample. Results are reported in table 7.

7. Concluding Remarks

In this paper, we have explored the causal relationship between international mobility and measures of overeducation and overskilling. Resorting to retrospective data on four cohorts of Italian PhD recipients, we have found that migration sizably reduces the odds of education and skill mismatch in the labor market. This suggests that by broadening the search area to foreign destinations, PhDs may successfully find better employment opportunities. Since PhD holders possess a set of occupation-specific skills whose returns occur only in a limited set of activities, and since the geographic distribution of high-skill occupations requires individuals to move to the areas in which the job opportunities are located, individual mobility turns out to pay off in terms of lower chances to be mismatched in the labor market.

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Table 1: Sample means by migrant status

	(1) Full sample	(2) Migrants	(3) Non-migrants	(4) Difference (3)-(2) b	se
PhD requested	0.519	0.141	0.587	0.446***	(0.013)
PhD requested/useful	0.260	0.099	0.280	0.181***	(0.009)
PhD needed	0.595	0.301	0.621	0.320***	(0.012)
Full R&D job	0.486	0.183	0.517	0.333***	(0.012)
Full/partly R&D job	0.312	0.131	0.329	0.198***	(0.009)
International mobility	0.082				
Wage ratio	1.072	1.387	1.044	-0.343***	(0.003)
# of new firms	11.493	11.938	11.453	-0.484	(0.263)
# of patents	0.139	0.163	0.136	-0.027***	(0.004)
# of firms	157.309	163.682	156.739	-6.944	(3.631)
Youth unempl. rate	16.663	15.663	16.753	1.089***	(0.230)
Female	0.503	0.374	0.515	0.141***	(0.012)
Age at PhD	0.261	0.422	0.247	-0.176***	(0.012)
Year = 2006	0.242	0.192	0.246	0.054***	(0.010)
Year = 2008	0.280	0.326	0.276	-0.050***	(0.012)
Year = 2010	0.259	0.341	0.252	-0.089***	(0.012)
Physics	0.037	0.106	0.030	-0.075***	(0.007)
Chemistry	0.050	0.061	0.049	-0.012*	(0.006)
Earth Sciences	0.024	0.019	0.024	0.005	(0.003)
Biology	0.085	0.086	0.085	-0.001	(0.007)
Medicine	0.148	0.103	0.152	0.049***	(0.008)
Agricultural and Veterinary Sciences	0.064	0.037	0.066	0.029***	(0.005)
Civil Engineering and Architecture	0.082	0.060	0.084	0.024***	(0.006)
Industrial and Information Engineering	0.125	0.186	0.119	-0.067***	(0.010)
Humanities	0.091	0.073	0.093	0.020**	(0.007)
Philosophy, Pedagogy and Psychology	0.089	0.063	0.091	0.028***	(0.006)
Law	0.082	0.040	0.085	0.045***	(0.005)
Economics and statistics	0.064	0.088	0.062	-0.026***	(0.007)
Political and social sciences	0.030	0.026	0.030	0.004	(0.004)
Married	0.577	0.471	0.586	0.116***	(0.012)
PhD_on_time	0.851	0.850	0.851	0.001	(0.009)
PhD scolarship	0.910	0.939	0.908	-0.031***	(0.006)
Father education is bachelor	0.315	0.355	0.311	-0.044***	(0.012)
Mother education is bachelor	0.241	0.274	0.238	-0.035**	(0.011)
Direct knowledge of the employer	0.066	0.082	0.065	-0.017*	(0.007)
Family/friends referral	0.045	0.030	0.046	0.015***	(0.004)
Professor referral	0.042	0.058	0.040	-0.018**	(0.006)
University referral	0.024	0.034	0.023	-0.011*	(0.004)
Internship or apprenticeship	0.042	0.044	0.042	-0.002	(0.005)
Direct call from a company	0.029	0.111	0.022	-0.090***	(0.008)
Internet and newspapers	0.137	0.281	0.124	-0.157***	(0.011)
Sending CVs	0.002	0.001	0.003	0.001	(0.001)
Self-employment	0.092	0.019	0.099	0.080***	(0.004)
Family firm	0.008	0.011	0.008	-0.003	(0.003)
Recruitment agency	0.049	0.041	0.050	0.009	(0.005)
Full time job	0.868	0.931	0.862	-0.069***	(0.007)

Table 2: Overeducation and overskilling

		PhD needed			Full/partly R&D job		
		yes (=0)	no (=1)	Total	yes (=0)	no (=1)	Total
PhD requested/useful	yes (=0)	5,537	4,349	9,886	7,724	2,162	9,886
	%	41.45	32.55	74.00	57.82	16.18	74.00
	no (=1)	211	3,262	3,473	1,439	2,034	3,473
	%	1.58	24.42	26.00	10.77	15.23	26.00
	Total	5,748	7,611	13,359	9,163	4,196	13,359
	%	43.03	56.97	100.00	68.59	31.41	100.00
Full/partly R&D job	yes (=0)	7,814	6,74	14,554			
	%	36.91	31.84	68.75			
	no (=1)	756	5,859	6,615			
	%	3.57	27.68	31.25			
	Total	8,57	12,599	21,169			
	%	40.48	59.52	100.00			

Table 3: IV tests

	Model				
Tests	PhD requested	PhD required/useful	PhD needed	Full R&D job	R&D Job (fully or partly)
Overidentification test of instruments					
Hansen J statistic	4.111	5.131	2.088	3.197	3.573
P-value	(0.3911)	(0.2741)	(0.7197)	(0.5255)	(0.4669)
Underidentification test					
Kleibergen-Paap rk LM statistic	1324.506***	1808.401***	2091.993***	1532.996 ***	2091.993 ***
Weak identification test					
Kleibergen-Paap rk Wald F statistic	1222.145***	1536.394***	1555.135***	1176.566 ***	1555.135 ***
Weak-instrument-robust inference					
Stock-Wright LM S statistic	178.99 ***	94.51***	203.95***	66.19***	40.45 ***

Figure 1 - Kernel-weighted local polynomial regression

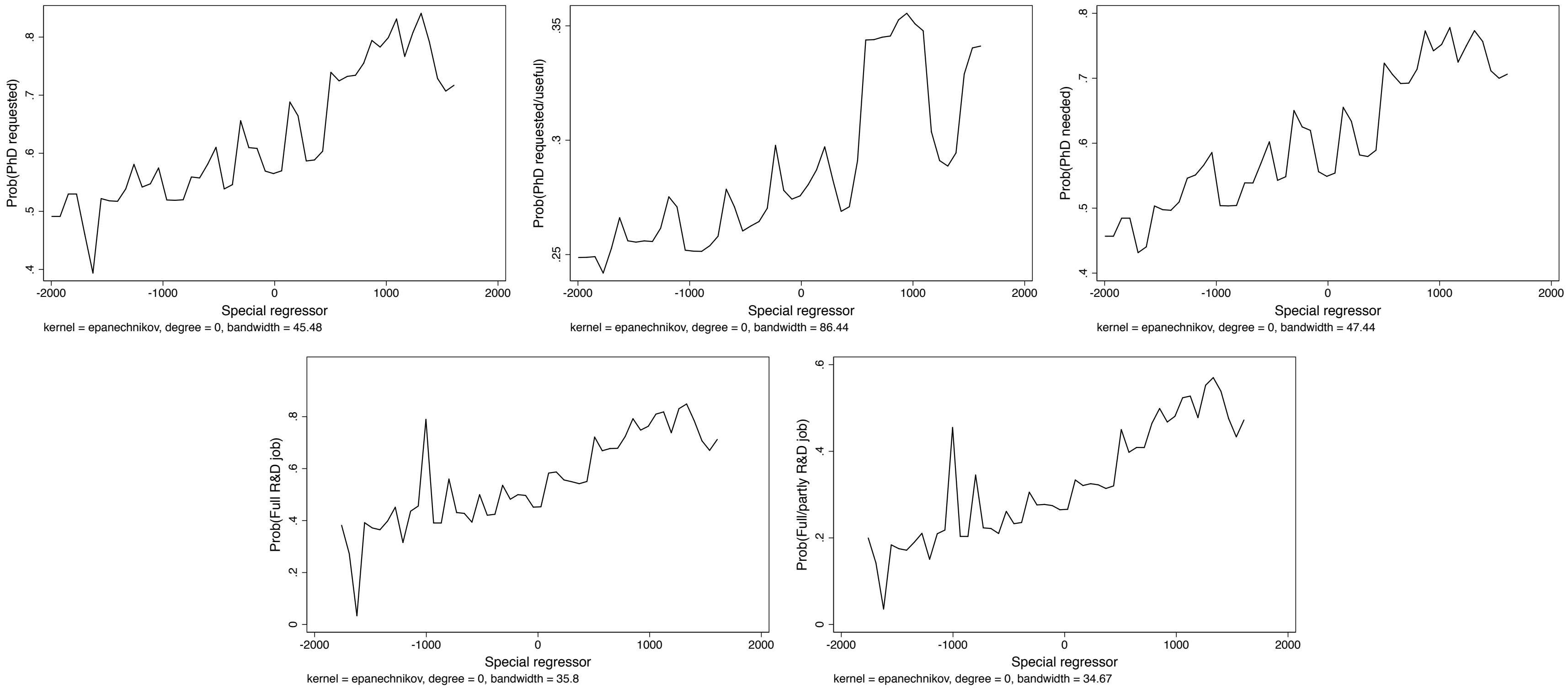

Table 4a: Bivariate probit

	(1)		(2)		(3)	
VARIABLES	PhD requested	Migration	PhD requested/useful	Migration	PhD needed	Migration
International mobility	-1.175***		-0.625***		-0.728***	
	(0.0918)		(0.0645)		(0.0476)	
Exclusion restrictions						
Wage ratio		9.709***		9.700***		9.508***
		(0.357)		(0.284)		(0.230)
# of new firms		0.147***		0.171***		0.146***
		(0.0394)		(0.0304)		(0.0256)
# of patents		1.902***		1.308***		1.334***
		(0.297)		(0.221)		(0.190)
# of firms		-0.011***		-0.012***		-0.010***
		(0.00294)		(0.00225)		(0.00189)
Youth unempl. rate		-0.0083**		-0.009***		-0.007***
		(0.00398)		(0.00300)		(0.00263)
Background characteristics						
Female	0.0810*	-0.155**	0.0943***	-0.209***	0.0880***	-0.186***
	(0.0461)	(0.0723)	(0.0283)	(0.0561)	(0.0211)	(0.0474)
Age at PhD	-0.103**	0.206***	-0.0830***	0.212***	-0.0406*	0.273***
	(0.0487)	(0.0690)	(0.0301)	(0.0538)	(0.0237)	(0.0465)
PhD on time	-0.124*	-0.272**	-0.0438	-0.182**	-0.104***	-0.123*
	(0.0754)	(0.107)	(0.0424)	(0.0815)	(0.0301)	(0.0657)
PhD scolarship	-0.133	0.0854	-0.117**	0.101	0.0497	0.136
	(0.0930)	(0.140)	(0.0498)	(0.103)	(0.0372)	(0.0870)
Father education is bachelor	0.0492	0.280***	0.0354	0.243***	0.0126	0.221***
	(0.0566)	(0.0819)	(0.0335)	(0.0613)	(0.0254)	(0.0521)
Mother education is bachelor	-0.0319	0.0414	-0.0514	0.0708	0.0184	0.0595
	(0.0596)	(0.0876)	(0.0359)	(0.0658)	(0.0274)	(0.0567)
Fields of study (base category is Mathematics)						
Physics	-0.0655	0.660***	0.0715	0.582***	0.0186	0.585***
	(0.167)	(0.242)	(0.112)	(0.170)	(0.0772)	(0.146)
Chemistry	-0.0361	0.110	0.118	0.0439	0.0174	0.0226
	(0.159)	(0.253)	(0.101)	(0.178)	(0.0723)	(0.159)
Earth Sciences	0.354*	-0.445	0.222*	-0.331	0.0755	-0.496
	(0.194)	(0.499)	(0.118)	(0.335)	(0.0881)	(0.315)
Biology	0.135	-0.0234	0.202**	0.0283	0.0908	0.0901
	(0.152)	(0.236)	(0.0950)	(0.165)	(0.0669)	(0.142)
Medicine	0.340**	-0.281	0.223**	0.00131	0.180***	-0.0169
	(0.152)	(0.234)	(0.0958)	(0.160)	(0.0660)	(0.135)
Agricultural and Veterinary Sciences	0.239	-0.420	0.198*	-0.214	0.112	-0.323**
	(0.167)	(0.277)	(0.102)	(0.178)	(0.0720)	(0.155)
Civil Engineering and Architecture	-0.0474	-0.395	0.0927	-0.251	-0.0231	-0.182
	(0.162)	(0.246)	(0.0989)	(0.176)	(0.0681)	(0.146)
Industrial and Information Engineering	0.0517	0.0140	0.0792	0.129	-0.0113	0.153
	(0.148)	(0.230)	(0.0935)	(0.155)	(0.0634)	(0.132)
Humanities	0.198	-0.187	0.264***	-0.122	2.14e-06	-0.0324
	(0.158)	(0.243)	(0.0963)	(0.168)	(0.0671)	(0.144)
Philosophy, Pedagogy and Psychology	0.255*	0.0256	0.309***	-0.0189	-0.00889	-0.0759
	(0.154)	(0.245)	(0.0960)	(0.174)	(0.0666)	(0.148)
Law	0.0934	-0.550*	0.163	-0.260	0.0886	-0.284*
	(0.164)	(0.283)	(0.102)	(0.189)	(0.0676)	(0.152)
Economics and statistics	-0.125	0.0727	0.0602	0.208	-0.156**	0.164
	(0.163)	(0.255)	(0.104)	(0.173)	(0.0698)	(0.143)
Political and social sciences	0.191	0.143	0.223*	0.253	-0.0387	0.262
	(0.191)	(0.284)	(0.116)	(0.197)	(0.0817)	(0.165)

Channel job (baseline category is public competition)						
Direct knowledge of the employer	0.492***		0.294***		0.168***	
	(0.0918)		(0.0564)		(0.0449)	
Family/friends referral	0.864***		0.563***		0.493***	
	(0.114)		(0.0621)		(0.0586)	
Professor referral	0.0967		-0.155**		-0.0931*	
	(0.123)		(0.0783)		(0.0536)	
University referral	0.824***		0.311***		0.189***	
	(0.154)		(0.0883)		(0.0689)	
Internship or apprenticeship	0.236**		0.0185		0.0356	
	(0.116)		(0.0684)		(0.0528)	
Direct call from a company	0.289**		0.202***		0.440***	
	(0.118)		(0.0739)		(0.0661)	
Internet and newspapers	0.431***		0.228***		0.238***	
	(0.0743)		(0.0447)		(0.0365)	
Sending CVs	7.278***		0.0822		0.172	
	(0.245)		(0.212)		(0.222)	
Self-employment	1.320***		0.567***		0.203***	
	(0.154)		(0.0587)		(0.0438)	
Family firm	0.741***		0.373***		0.725***	
	(0.245)		(0.119)		(0.137)	
Recruitment agency	0.669***		0.160**		0.208***	
	(0.129)		(0.0622)		(0.0511)	
Full time job	-0.232***		-0.231***		-0.235***	
	(0.0739)		(0.0375)		(0.0330)	
Constant	-1.240***	-12.73***	-1.695***	-13.03***	-0.849***	-12.99***
	(0.222)	(0.528)	(0.134)	(0.421)	(0.0942)	(0.343)
Correlation of error terms	0.0725		0.0924		0.0610	
	(0.0771)		(0.0564)		(0.0435)	
Observations	6,693	6,693	13,359	13,359	21,169	21,169
Province FE	YES	YES	YES	YES	YES	YES
Cohort FE	YES	YES	YES	YES	YES	YES
Sector FE	YES	NO	YES	NO	YES	NO

Table 4b: Bivariate probit

	(1)		(2)	
VARIABLES	Full R&D job	Migration	Full/partly R&D job	Migration
International mobility	-0.632***		-0.418***	
	(0.0719)		(0.0562)	
Exclusion restrictions				
Wage ratio		9.590***		9.510***
		(0.289)		(0.230)
# of new firms		0.136***		0.146***
		(0.0313)		(0.0255)
# of patents		1.078***		1.330***
		(0.235)		(0.190)
# of firms		-0.00918***		-0.00999***
		(0.00231)		(0.00189)
Youth unempl. rate		-0.00898***		-0.00711***
		(0.00308)		(0.00263)
Background characteristics				
Female	0.126***	-0.233***	0.135***	-0.185***
	(0.0301)	(0.0568)	(0.0213)	(0.0473)
Age at PhD	-0.0634*	0.270***	0.00209	0.272***
	(0.0327)	(0.0558)	(0.0248)	(0.0466)
PhD on time	-0.0719	-0.0536	-0.0176	-0.122*
	(0.0452)	(0.0865)	(0.0299)	(0.0658)
PhD scolarship	0.0603	0.199*	0.00712	0.134
	(0.0524)	(0.115)	(0.0359)	(0.0866)
Father education is bachelor	0.0659*	0.211***	0.00585	0.222***
	(0.0358)	(0.0641)	(0.0253)	(0.0520)
Mother education is bachelor	-0.132***	0.0986	-0.0795***	0.0602
	(0.0388)	(0.0693)	(0.0274)	(0.0567)
Fields of study (base category is Mathematics)				
Physics	-0.327***	0.591***	-0.106	0.591***
	(0.109)	(0.170)	(0.0855)	(0.147)
Chemistry	-0.252**	-0.0778	0.0133	0.0229
	(0.100)	(0.188)	(0.0779)	(0.160)
Earth Sciences	0.136	-0.642	-0.00443	-0.493
	(0.126)	(0.427)	(0.0922)	(0.317)
Biology	-0.0730	0.0335	0.125*	0.0949
	(0.0954)	(0.165)	(0.0724)	(0.143)
Medicine	-0.0118	-0.0626	-0.0280	-0.0125
	(0.0946)	(0.160)	(0.0722)	(0.136)
Agricultural and Veterinary Sciences	-0.0305	-0.410**	0.0962	-0.325**
	(0.100)	(0.186)	(0.0769)	(0.156)
Civil Engineering and Architecture	0.0690	-0.161	-0.0569	-0.173
	(0.101)	(0.178)	(0.0741)	(0.146)
Industrial and Information Engineering	-0.166*	0.0980	-0.0876	0.158
	(0.0921)	(0.158)	(0.0707)	(0.133)
Humanities	0.0722	-0.192	-0.141*	-0.0222
	(0.103)	(0.183)	(0.0731)	(0.145)
Philosophy, Pedagogy and Psychology	-0.0793	-0.167	-0.188***	-0.0679
	(0.101)	(0.183)	(0.0730)	(0.148)
Law	-0.261**	-0.450**	-0.261***	-0.278*
	(0.102)	(0.200)	(0.0751)	(0.152)
Economics and statistics	-0.171	0.112	-0.156**	0.170
	(0.105)	(0.176)	(0.0784)	(0.144)
Political and social sciences	0.0995	0.141	-0.121	0.269
	(0.126)	(0.220)	(0.0901)	(0.165)
Channel job (baseline category is public competition)				
Direct knowledge of the employer	-0.0870		-0.0238	
	(0.0648)		(0.0454)	
Family/friends referral	0.500***		0.362***	

	(0.0793)		(0.0509)	
Professor referral	-0.312***		-0.231***	
	(0.0819)		(0.0606)	
University referral	-0.0830		-0.0181	
	(0.0963)		(0.0681)	
Internship or apprenticeship	-0.0297		-0.0303	
	(0.0782)		(0.0518)	
Direct call from a company	0.335***		0.334***	
	(0.0853)		(0.0628)	
Internet and newspapers	0.249***		0.218***	
	(0.0519)		(0.0355)	
Sending CVs	0.377		0.613***	
	(0.289)		(0.192)	
Self-employment	0.142**		-0.0436	
	(0.0655)		(0.0415)	
Family firm	0.906***		0.667***	
	(0.160)		(0.110)	
Recruitment agency	0.381***		0.291***	
	(0.0747)		(0.0467)	
Full time job	-0.436***		-0.343***	
	(0.0493)		(0.0302)	
Constant	-1.256***	-13.10***	-1.282***	-13.00***
	(0.139)	(0.429)	(0.101)	(0.344)
Correlation of error terms	-0.0614		-0.0227	
	(0.0679)		(0.0513)	
Observations	13,604	13,604	21,169	21,169
Province FE	YES	YES	YES	YES
Cohort FE	YES	YES	YES	YES
Sector FE	YES	NO	YES	NO

Table 5 - Marginal Effects

	(1)	(2)	(3)	(4)	(5)
	PhD requested	PhD required/useful	PhD needed	R&D Job	R&D Job (fully or partly)
Bivariate probit	-0.201***	-0.158***	-0.200***	-0.130***	-0.117***
	(0.0148)	(0.0162)	(0.0127)	(0.0146)	(0.0156)
Observations	6,693	13,359	21,169	13,604	21,169
2SRI	-0.207***	-0.160***	-0.199***	-0.131***	-0.117***
	(0.0155)	(0.0166)	(0.0124)	(0.0142)	(0.0151)
Observations	6,640	13,353	21,169	13,604	21,169
Special regressor	-0.134***	-0.0842***	-0.145***	-0.0878***	-0.0636***
	(0.0236)	(0.0172)	(0.0203)	(0.0208)	(0.0213)
Observations	6,692	13,358	21,168	13,604	21,168

Bootstrapped standard errors in parentheses (199 replications).
*** p<0.01, ** p<0.05, * p<0.1

Table 6 – Marginal effects by cohort

	(1) PhD requested	(2) PhD requested/useful	(3) PhD needed	(4) R&D	(5) R&D Job (fully or partly)
Bivariate probit					
Year=2004	-0.205***	-0.163***	-0.183***	-0.138***	-0.161***
	(0.0444)	(0.0412)	(0.0349)	(0.0389)	(0.0448)
Observations	1,543	3,344	4,641	3,275	4,641
Year=2006	-0.252***	-0.167***	-0.229***	-0.161***	-0.125***
	(0.0380)	(0.0374)	(0.0331)	(0.0336)	(0.0340)
Observations	1,558	3,283	5,114	3,480	5,114
Year=2008	-0.173***	-0.129***	-0.151***	-0.114***	-0.115***
	(0.0266)	(0.0300)	(0.0207)	(0.0244)	(0.0275)
Observations	1,955	3,692	5,932	3,601	5,932
Year=2010	-0.189***	-0.200***	-0.204***	-0.124***	-0.115***
	(0.0233)	(0.0289)	(0.0198)	(0.0255)	(0.0283)
Observations	1,637	3,040	5,482	3,248	5,482
2SRI					
Year=2004	-0.243***	-0.172***	-0.180***	-0.138***	-0.158***
	(0.0510)	(0.0438)	(0.0362)	(0.0385)	(0.0426)
Observations	1,512	3,338	4,641	3,268	4,634
Year=2006	-0.265***	-0.175***	-0.222***	-0.159***	-0.120***
	(0.0402)	(0.0383)	(0.0328)	(0.0339)	(0.0345)
Observations	1,534	3,272	5,112	3,479	5,114
Year=2008	-0.176***	-0.127***	-0.153***	-0.115***	-0.117***
	(0.0267)	(0.0283)	(0.0197)	(0.0232)	(0.0266)
Observations	1,900	3,684	5,920	3,591	5,925
Year=2010	-0.193***	-0.203***	-0.200***	-0.132***	-0.122***
	(0.0222)	(0.0306)	(0.0189)	(0.0236)	(0.0261)
Observations	1,611	3,034	5,474	3,222	5,478
Special regressor					
Year=2004	-0.128**	-0.0415	-0.0874*	-0.0546	-0.0540
	(0.0649)	(0.0323)	(0.0481)	(0.0567)	(0.0461)
Observations	1,543	3,344	4,641	3,275	4,641
Year=2006	-0.182***	-0.0587**	-0.139***	-0.131***	-0.120***
	(0.0526)	(0.0287)	(0.0390)	(0.0439)	(0.0391)
Observations	1,557	3,282	5,113	3,480	5,113
Year=2008	-0.111***	-0.0547*	-0.106***	-0.0695	-0.0547
	(0.0383)	(0.0314)	(0.0340)	(0.0435)	(0.0336)
Observations	1,955	3,692	5,932	3,601	5,932
Year=2010	-0.121***	-0.124***	-0.143***	-0.0807**	-0.0523*
	(0.0356)	(0.0267)	(0.0276)	(0.0353)	(0.0301)
Observations	1,637	3,040	5,482	3,248	5,482

Table 7 - Marginal effects STEM PhD graduates

	(1) PhD requested	(2) PhD requested/useful	(3) PhD needed	(4) R&D	(5) R&D Job (fully or partly)
Bivariate probit	-0.218***	-0.174***	-0.204***	-0.108***	-0.0985***
	(0.0179)	(0.0201)	(0.0159)	(0.0166)	(0.0184)
Observations	3,684	7,271	10,511	7,264	10,511
2SRI	-0.222***	-0.177***	-0.205***	-0.110***	-0.100***
	(0.0190)	(0.0205)	(0.0154)	(0.0166)	(0.0176)
Observations	3,651	7,262	10,511	7,264	10,511
Special regressor	-0.153***	-0.0686***	-0.148***	-0.101***	-0.0663***
	(0.0230)	(0.0200)	(0.0200)	(0.0357)	(0.0230)
Observations	3,684	7,271	10,511	7,264	10,511

Table 8 - Marginal effects PhD graduates employed in the private sector (N=5851)

	(1) PhD requested	(2) PhD requested/useful	(3) PhD needed	(4) R&D	(5) R&D Job (fully or partly)
Bivariate probit	-0.1746***	-0.1793***	-0.1660***	-0.1083***	-0.0599**
	(0.0195)	(0.0309)	(0.0192)	(0.0277)	(0.0287)
2SRI	-0.1780***	-0.1773***	-0.1637***	-0.1149***	-0. 0627**
	(0.0181)	(0.0320)	(0.0185)	(0.0256)	(0.0267)
Special regressor	-0.1413***	-0.1099***	-0.1207***	-0.1028***	-.0425
	(0.0346)	(0.0286)	(0.0182)	(0.0355)	(0.0302)