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The returns to temporary migration: The case of Italian Ph.D.s

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Abstract

This paper examines the implications of temporary migration episodes for two cohorts of Italian Ph.D.s. Special attention is given to the duration of experience abroad, its contribution to earned wages and the selectivity of returnees. After controlling for the endogeneity of both the migration decision and the length of stay abroad, we find positive returns to longer periods abroad and negative returns to shorter periods. Returnees are also found to be positively self-selected. The results are confirmed in several robustness and sensitivity checks.

JEL codes: J3, J61, F22
Keywords: skilled migration, return migration, migration premium, self-selection

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1 Introduction

The rising trend in skilled migration flows has significantly renewed the interest of scholars and policy makers on topics related to the brain drain, brain gain and brain circulation (Beine et al. 2011; Docquier & Rapoport 2012). As skilled labor migration produces considerable knowledge flows among countries, with obvious repercussions on aggregate productivity, innovation and growth (Peri et al. 2015), many countries have adopted quality-selective immigration policies, such as tax benefits and simplified immigration measures[1] aimed at attracting talents on a global scale (Beine et al. 2008).

At the micro level, as part of an optimal life-cycle planning, individuals engage in mobility patterns to reach the locations in which skills can be acquired effectively and/or are better rewarded. In this context, college and university graduates have become a key group in the research on high skilled migration (Faggian & McCann 2009; Haapanen & Tervo 2011; Corcoran et al. 2010; Venhorst et al. 2011; Groen 2004). Nevertheless, the literature has so far mainly focused on episodes of permanent migration and has overlooked the mobility of individuals holding post-graduate degrees. This paper is intended to study these two largely unexplored dimensions by investigating the role of temporary international migration in post-education periods for individual wages of two cohorts of Italian Ph.D. holders.

Our focus on doctorate holders is motivated on several grounds. Ph.D.s are among the most qualified workers in the economy, as they are endowed with high levels of human capital. They contribute to the dissemination of knowledge, are often employed in innovative sectors and play a crucial role for economic development. Furthermore, Ph.D.s are trained in academic environments open to international exchanges, and this makes doctorate holders a peculiar population to scrutinize in terms of post-education mobility choices. Moreover, the labor market for doctorate holders has changed both quantitatively and qualitatively. While in the past decades the worldwide development of higher education systems has yielded a growing number of students receiving a doctorate degree,[2] opportunities for academic employment have grown at slower rates, with an increasing number of Ph.D.s employed in the private sector (Garcia-Quevedo et al. 2011).

[1] The EU Council Directive 2009/50/EC introduced the Blue Card, a simplified work-permit allowing high-skilled non-EU citizens to work in EU countries.

[2] For instance, Auriol et al. (2013) document a 38% growth in the number of Ph.D.s graduated from universities in OECD countries over the period 2000-2009. For the Italian case, the National Institute of Statistics (ISTAT) has documented that in 2000 around 4000 students were granted a Ph.D. degree, while the number had risen to over 12000 after only 8 years.

Then, to the extent that learning and employment opportunities are geographically distributed at a national and international level, early mobility patterns may facilitate better job matches in the labor market for Ph.D.s.

This paper is also specifically concerned with episodes of return migration. Despite the well known measurement difficulties to assess the real magnitude of returnee flows among migrants (Dustmann & Weiss 2007; Ambrosini et al. 2015), the literature has recognized the importance of return migration as a possible channel through which source countries may benefit from international migration.[3] While abroad, individuals may enhance their human capital endowment (Dustmann et al. 2011), accumulate financial assets and assimilate valuable cultural and social norms (Bertoli & Marchetta 2015). Then, upon return, they might enjoy significant wage premia (Reinhold & Thom 2013; Coulon & Piracha 2005; Co et al. 2000) or successfully undertake entrepreneurial activities (McCormick & Wahba 2001; Dustmann & Kirchkamp 2002; Marchetta 2012). In the case of doctorate holders, experience abroad can also be part of an investment plan aimed at increasing their *scientific* capital stock, reputation or involvement in scientific networks, all of which may facilitate their careers in both private and public institutions in the domestic labor market.

Beside the motivations that trigger migratory paths, a crucial factor, yet mostly neglected in previous research, is the length of time individuals decide to spend abroad. Empirical models implemented in the migration literature often deal with the dichotomous choice faced by migrants, but do not consider the length of time spent in other countries. Nevertheless, human capital theory suggests that observed outcomes in the labor market are likely to reflect the investment made by individuals, which is obviously a time-consuming activity. It follows that rewards to foreign experiences may depend also on how long individuals decide to remain in a foreign country.

This paper contributes to the existing literature in several ways. First, we document the size and composition of the return migration flow for the population of Italian Ph.D.s. Second, we show that failing to account for the spell of experience abroad would produce misleading estimates of the impact of mobility on individual wages, as the true effect strongly depends on the time spent abroad. Third, this study addresses the endogeneity of both the returnee status and the duration of the stay abroad and concludes that each choice need to be considered as endogenous by practitioners to capture selectivity among returnees. In detail, this paper is the first documenting positive selection of temporary Ph.D. migrants and even stronger positive selection related to the length of stay abroad.

[3] Other possible benefits are related to remittances. See the discussion in Docquier and Rapoport (2006), Hatton (2014) and suggested references.

Furthermore, the paper delivers estimates of the return to experience for economic relevant sub-populations, such as male/female and academic/non-academic employment.

The implication of our findings should be evaluated in light of the on-going academic and policy debate focused on the international competition for talents (Docquier & Machado 2015). If the net growth of the domestic high skilled population is slow, negative repercussions can be expected for firms and countries alike, as firms' ability to innovate and succeed strongly depends on the quality of the available workforce. Returnees compensate the original outflow of skilled workers

We also wish to acknowledge upfront some limitations that should be borne in mind when interpreting the results. High-achievers in the education system are only part of the high skilled migrant population. Thus, the results can not be slavishly extended to the whole category of skilled returnees. Yet, we believe Ph.D. holders deserve a specific research focus due to their importance in the creation and diffusion of scientific knowledge on a global scale. This study has also some data limitations. First, data are retrospective and do not provide all the details related to the period of time spent abroad, such as earnings and employment characteristics. Second, even if the data reports the exact length of stay in months, individuals were not asked about the starting date of the period.

The rest of the paper is organized as follows. Section 2 is concerned with the positioning of the paper in the relevant literature. Section 3 describes the empirical model. Section 4 contains a brief description of the data along with summary statistics. Results and robustness checks are presented and discussed in section 5. Section 6 concludes.

2 Background and related literature

The scientific debate of migration is traditionally framed into the human capital theory, as firstly discussed in Sjaastad (1962) and Becker (1962), and most theoretical models of migration (and their empirical implementations) have been predominantly developed to explain permanent location changes. However, migration can also be a reversible decision that brings individuals back to their country of origin. [4] In this respect, several authors have so far contributed to provide theoretical underpinnings to the decision-making of returnees. In early contributions of Hill (1987) and Djajić (1988), return migration results from the balancing of the trade off between higher wages enjoyed while abroad and forgone utility related to higher preferences for home consumption. Thus,

[4] Research has also investigated other forms of migration. A formal taxonomy can be found in Dustmann and Weiss (2007).

even if lifetime income would be higher by remaining in a guest country, individuals maximize their lifetime utility by spending some time in the host country and then returning home. Nevertheless, return migration is observed also in the absence of a reversal of the relative wages of the sending and receiving countries (Stark et al. 1997), and its rational may well depend on other factors, such as target-savings motives (Berninghaus & Seifert-Vogt 1989), higher purchasing power in the home country (Stark et al. 1997), credit constraints (Mesnard 2004) and unfulfilled expectations about opportunities in the host country (Borjas & Bratsberg 1996).

As the present research is focused on doctorate holders, human capital considerations turn out to be of particular interest. If returns to human capital investments made in the host country are higher in the home country, some individuals may decide to relocate to their country of origin (Dustmann 1997). Moreover, knowledge and skills could be acquired abroad more efficiently or faster than in the home country (Dustmann et al. 2011). Interestingly, since human capital grows over time, the length of time spent abroad is potentially a key factor in explaining the impact of return migration on labor market outcomes at home. Thus, in contrast to Borjas and Bratsberg (1996) who assume that learning abroad raises local earning by a fixed proportion irrespectively of the duration of the stay abroad, other scholars have extended the reference framework to the case of human capital growth over time (Dustmann & Weiss 2007; Santos & Postel-Vinay 2003; Coulon & Piracha 2005). This view has been explored both theoretically and, to a lesser extent, empirically. In Dustmann (2002), migration duration and after-migration activities are optimally chosen to maximize lifetime utility.[5] The model predicts that planned duration responds to changes in host- and home country wages and that the behavioral response varies according to the post-migration activity. Mayr and Peri (2009) develop a model of optimal human capital investments, migration and return migration as functions of personal abilities to analyze the effects of migration policies on human capital and wages in sending countries. Notably, the model stresses the importance of human capital accumulation and its economic returns in shaping different individual migration patterns. Yet, longer spells of temporary migration may also be associated to worse outcomes in the domestic labor market. To the extent that individuals loose valuable social capital while abroad (Marchetta 2012), return migration would deteriorate the performance of returnees. Also, if skills acquired abroad have limited transferability across borders, individuals may accept under-qualified jobs in the home country upon return. In a recent study on graduate (internal) migration, Di Cintio and Grassi (2011) find that individuals

[5] In particular, the author suggests how changes in the wages in the host- and home country can have different effects on the migration duration, but is not able to fully confirm theoretical predictions with the data.

choosing to move back home to work (instead of remaining in the area of study) experience a wage loss that is roughly equal to the opposite of the difference between the wage of individuals holding a job in the same province where they moved to study and the wage of those who never moved. The authors point out that if these movers obtain a rent because of mobility, back movers choose to give up this rent by returning to the area of origin.

Empirical evidence of the effects of return migration for international mobile individuals is growing rapidly, but it is largely focused on the experience of less developed countries. Reinhold and Thom (2013) use data on migrants who return to Mexico after spending some time in the United States and estimate an earning increase of approximately 2-3% for every year spent abroad. Co et al. (2000) focus on Hungarian data and find a 40% earning premium for female returnees while no effect is found for men. Differently, Barrett and O'Connell (2010) report a 7% wage premium for both genders, which is increasing with education attainments.[6] Ambrosini et al. (2015) analyzes Romanian data and find that not only returnees enjoy higher wages but also that the premium is increasing with their level of skills.

The present study also stands within the on-going debate concerning the mobility of college and university graduates. Both doctorate holders and graduates leave the education system with a higher than average human capital endowment and feel the urgency of making this investment paying off also through further investments in mobility patterns (Venhorst et al. 2011; Di Cintio & Grassi 2016). In this respect, increasing evidence suggesting positive economic returns to migration have been documented mostly for internal migration patterns,[7] while few studies have tried to shed light on the mobility of Ph.D. recipients and their performance in the labor market. Indeed, while the *research* performance of Ph.D.s have attracted the attention of many scholars (Athey et al. 2007; Grove & Wu 2007), only recently the international migration literature has started examining the mobility of doctorate holders. In particular, it has been shown how the propensity to migrate responds to age and gender differences (Di Cintio & Grassi 2016), the type of jobs Ph.D.s are willing to accept (Davis & Patterson 2000), the presence of both amenity factors (Gottlieb & Joseph 2006) and world-leading research organizations (Grogger & Hanson 2015). We extend this discussion by deepening the understanding of the labor market outcomes associated to episodes of temporary migration of doctoral holders.

[6] A summary of further empirical evidence for developing countries can be found in Mayr and Peri (2009).
[7] See, among others, Abreu et al. (2015) and Di Cintio and Grassi (2011).

3 Research methods

We start with an empirical framework in which (log) wages for temporary migrants y_{i1} and non-migrants y_{i0} are related to a set of explanatory variables associated to both personal and job characteristics x_{ij}, so that:

$$\begin{aligned} y_{i1} &= \mu_1 + \beta_1' x_{i1} + \gamma temp_i + u_{i1} \\ y_{i0} &= \mu_0 + \beta_0' x_{i0} + u_{i0} \end{aligned}, \tag{1}$$

where μ_j are scalars, β_j and γ are parameters to be estimated, $temp$ is the number of months the $i-th$ individual has spent abroad after the Ph.D. and u_{ij} are error terms. Coherently with the literature on program evaluation originally developed by Rubin (1974) and Holland (1986), the previous set up can be interpreted in terms of two mutually exclusive outcomes associated to program participation. Here, an evaluation problem arises, for the researcher can only observe the wage of the realized outcome, so that the observed wage can be read as follows:

$$y_i = y_{i0} + t(y_{i1} - y_{i0}), \tag{2}$$

where t is the binary indicator for temporary migration experience. By plugging equations 1 in equation 2, the following wage equation is immediately derived:

$$y_i = \mu_0 + \beta_0' x_{i0} + u_{i0} + t(\mu_1 - \mu_0) + t\gamma temp_i + t(\beta_1' x_{i1} - \beta_0' x_{i0}) + t(u_{i1} - u_{i0}). \tag{3}$$

As a starting point for discussion, we assume a homogenous treatment response ($\beta_1 = \beta_0 = \beta$) and a homogenous erratic component ($u_1 = u_0 = u$). Furthermore, we initially neglect the effect of the length of stay abroad, so that equation 3 collapses to:

$$y_i = \mu_0 + \beta' x_i + t(\mu_1 - \mu_0) + u_i. \tag{4}$$

Even in this simplified setting, internal validity is threatened by the fact that temporary migrants are self-selected rather than randomly assigned. Thus, in the absence of an exogenous source of variation of the incentive to migrate, the binary indicator of mobility is strongly suspected of endogeneity, i.e. individuals chose to migrate only to the extent that the expected benefits associated with this choice is no less than the costs of moving (Sjaastad 1962; Borjas 1987).[8] To tackle this problem, we implement an endogenous binary treatment version of Heckman's (1976; 1979) two-step model,[9] where the observed migration choice depends from an unobservable latent variable t^* that is assumed to be linearly related to a set of covariates, z_i, so that:

$$t_i^* = \alpha' z_i + e_i \qquad (5)$$

and

$$t_i = \begin{cases} 1 & \text{if } t_i^* > 0 \\ 0 & \text{otherwise} \end{cases}, \qquad (6)$$

where equation (6) is the selection rule. We estimate model 4, 5 and 6 within a two-step framework derived in Maddala (1986) in which individuals differ in unobservable ways that contribute to determine both selection into migration and the effect of migration. Thus, we control for selection in a mincerian-type regression by estimating a selection rule (with and without exclusion restrictions) that predicts whether a Ph.D. graduate migrates abroad.

The two-step estimator relies on the assumption that the unobserved heterogeneity is captured by the correlation structure between u_i and e_i, i.e. the correlation between unobservables affecting t and unobservables affecting y. In particular, u_i and e_i are bivariate normal distributed with correlation coefficient ρ. Estimation proceeds as follows. First, we obtain probit estimates of the form:

$$Pr(t_i = 1|z_i) = \Phi(\alpha' z_i) \qquad (7)$$

and, then, we recover the hazard h for each observation according to the formula:

$$h_i^t = \begin{cases} \phi(\widehat{\alpha}' z_i)/\Phi(\widehat{\alpha}' z_i) & t_i = 1 \\ -\phi(\widehat{\alpha}' z_i)/\{1 - \Phi(\widehat{\alpha}' z_i)\} & t_i = 0' \end{cases} \qquad (8)$$

[8] A different possible shortcoming is related to the fact that individuals self-select into employment. As commonly pointed out in many empirical studies, if wages are only observed for individuals that actually have a job, then sample selection bias arises. However, in our study, we believe that this source of bias should play a little role due to the small number of unemployed individuals. Precise numbers are given in section 4.

[9] An alternative approach would be to model the migration decision in a multinomial context and correct for selectivity in a more accurate way as in Lee (1983) and Dahl (2002). Unfortunately, the number of observations for each possible destination is too low given the small fraction of movers in our data. Thus, we decided to apply a simpler model that is still able to account for selectivity.

where ϕ and Φ are, respectively, the probability and cumulative density functions. The estimates of β, $(\mu^1 - \mu^0)$ are then obtained by augmenting the regression equation with h^t:

$$y_i = \mu_0 + \beta' x_i + t_i(\mu_1 - \mu_0) + \rho\sigma_i h_i^t + u_i. \quad (9)$$

Note that, the parameter associated with the hazard is the product of the standard deviation parameter (σ, which is always positive) and the correlation coefficient (ρ) between the error terms of the wage and the selection equations, thus it is informative about the strength of the unobserved heterogeneity in our data. A positive correlation coefficient implies positive selection into migration due to unobservable traits that induce, at the same time, higher observed wages. Contrary, a negative correlation coefficient is symptomatic of negative selection, i.e. individuals who are low earners are endowed with unobserved traits that make them also more likely to migrate.

In the set up developed so far, the impact of mobility is captured as a level shift by the estimate of $(\mu_1 - \mu_0)$. However, as discussed in the previous section, individuals are likely to differ in their marginal costs and benefits of migration in a way that lead them to opt for different length of stay abroad. Migration duration is then an additional source of identification of the gains/losses experienced after re-migration. Thus, the next step is to consider the possible relationship between wages and the duration of stay abroad. However, also the length of stay may be endogenous and we assume that first a decision to move has to be taken and then the length of stay is decided. We implement a Heckman two-step protocol in which the probit model in equation (9) is used to recover the Mill's ratio ($m_i = \phi(\widehat{\alpha}' z_i)/\Phi(\widehat{\alpha}' z_i)$), then the variable $temp$ is regressed on a set of covariates, w_i, and m_i:

$$temp_i = \gamma' w_i + \theta m_i + v_i. \quad (10)$$

From this step we obtain the selection-corrected estimates of the length of stay abroad, $\widehat{temp}_i$, which augments the wage equation in (9) to obtain the estimates of $(\mu^1 - \mu^0)$ and γ:

$$y_i = \mu_0 + \beta' x_i + t_i(\mu_1 - \mu_0) + t_i \gamma \widehat{temp}_i + \rho\sigma_i h_i^t + u_i\,. \quad (11)$$

In this way, the expected impact of temporary migration depends also on the duration of stay and the estimates control for both sources of endogeneity.

4 Data description

The empirical analysis uses data from the second Professional Integration Survey of PhDs (*Indagine sull'inserimento professionale dei dottori di ricerca*) administered by the Italian National Institute of Statistics (ISTAT) on Italian Ph.D. graduates. In particular, the survey[10] has been conducted between February and May 2014 with the aim of gathering information on the labor market entry conditions of two cohorts of doctorates who received a degree from an Italian university in 2008 and 2010, respectively. The survey questionnaire is articulated in five sections. The first one is about individual curricula and the characteristics of the attended Ph.D. program; the second section covers job characteristics; the third is directed to job searchers to understand features of their job search process; the fourth section asks for retrospective patterns of geographic mobility; the fifth collects pieces of information about current as well as origin family status.

The survey has been administered to the universe of Ph.D.s. In detail, on a population of 22,459 individuals (11,229 in 2008 and 11,240 in 2010), 16,322 interviews were made (7,888 doctors in 2008 and 8,434 in 2010), with an overall response rate of 72.64%. More than 92% of Ph.D.s report to have a job at the time of the interview. Moreover, among those without a job, around 27% reported being waiting to start a new job or attending some training program before the job starts. It follows that the fraction of unemployed Ph.D.s is very low. For this reason, we consider the bias associated with selection into jobs being very low in our data and restrict the analysis to individuals holding a job.

We define *return migrants* all the individuals who report having spent a period of time[11] in a foreign country after the Ph.D. Similarly to Reinhold and Thom (2013), while we keep data for non-migrants and return migrants, we exclude individuals who have migrated to a foreign country, but have not returned to Italy at the date of the interview. We also drop observations with missing information on important variables such as wages, hours worked or other job characteristics. The resulting size of the dataset is 8,981 observations.

Table 1 presents descriptive statistics for log earnings, migration status and duration along with the variables used in the analysis. The statistics are further broken down by migrant status in subsequent columns. Return migrants represent around 12.4% of the selected population and have accumulated about 12 months of experience abroad. Interestingly, the sub-populations of returnees and stayers differ along several

[10] Graduates were interviewed by a computer-assisted web interviewing (CAWI).

[11] Our definition of returnees takes into account the fact that respondents were asked if they had spent at least three consecutive months abroad after the Ph.D.

dimensions. The proportion of females among mobile individuals is 46.6%, even if, overall, the share of females is 53.7%, suggesting that, on average, males tend to be more mobile than females. At the same time, there are no sensible gender differences in the average time spent abroad, as male returnees stay only one month more in a foreign country. Moreover, returnees are more likely to report both previous experiences abroad during their studies and past inter-regional mobility to attend the Ph.D. A sharp difference between temporary migrants and non-migrants is related to the age at which the Ph.D. was awarded. Indeed, while among returnees 89.3% graduated before turning 35, only 73.7% of stayers graduated before 35. Nevertheless, there is not a substantial difference between the two groups in the percentage of individuals graduating on time. This suggests that stayers were on average older when they enrolled in the Ph.D. program. Interestingly, return migrants seem to enjoy better job-matches (71% of them report that the Ph.D. was requested for the job, while only 44.6% of stayers report the same; more than 86% of movers perform R&D related activities in their jobs, while only 71% of stayers report the same) and have a higher scientific productivity, measured by the number of articles and patents.[12] Finally, returnees have lower job experience compared to stayers and it is less likely that they were working at the time of their degrees.

Neglecting the duration of temporary international experiences, rough unconditional figures reveal that migrants earn around 3.7% more than non-migrants. However, if we compare average individual wages computed at different length of stay, the picture is different. Table 2 shows that individuals who spent less than one year in a foreign country tend to earn as much as those who never migrated. Conversely, those who choose to remain abroad for longer periods seem to enjoy increasing wage gains. On average, a duration between one and two years is associated with a 7.5% higher wage, a duration between two and three years with a 13.2% increase and a duration of at least four years with a 27%increase.

In the rest of the paper, we try to assess to what extent this pattern mirrors a causal link between duration abroad and domestic earning.

5 Estimation results

OLS estimates of the relationship between log wages and temporary migration are shown in the first column of table 3. The main regressors of interest are a dummy for the migration experience and the number of months spent abroad, both are treated as

[12] Note that the questionnaire did not ask to report how many articles where actually published in peer-reviewed or top journals, but only the rough number.

exogenous variables. While we only report the estimates with the full set of control variables, in more parsimonious specifications of the empirical model[13] two interesting patterns emerge. First, as we progressively add more controls, the magnitude of the coefficient on the indicator of temporary migration tends to fall. Since some of the controls that we incrementally add are potentially correlated to unobservable individual traits, the endogeneity bias in OLS estimates is likely to be severe and the estimated impact of temporary migration is confounded with the effects of unobserved characteristics. Second, also the coefficient of the migration duration is declining across different model specifications, suggesting that there is a specific source of selection bias that might not be fully captured by solving the endogeneity problem of the dichotomous variable alone.[14] We thus expect differences between the estimates of the endogenous dummy variable model and the estimates from the model in which we endogenize also the migration duration.

Regression results also reveal that other observed characteristics are important predictors of wages in accordance with previous literature. In detail, we find that females earn around 9% less than males. Wages are decreasing in age at Ph.D. and are higher for those who received their doctorate degree from northern universities. As expected, we find diminishing returns to work experience, with a positive coefficient on the linear term and a negative coefficient on the quadratic term. Proxies for the job-match quality indicate higher wages for those carrying out R&D activities in their job and for those employed in jobs for which the Ph.D. was required. Having completed the Ph.D. on time has also a positive impact on wages, as employers might interpret it as a signal of efficiency and commitment.

To explore in detail issues related to selectivity of migrants, we start with the estimation of the endogenous dummy variable model described by equation 9. In particular, we first discuss the results of the migration equation (table A1 in the Appendix) and then we move to the analysis of the earning equation (table 3, column 2). In line with previous research, the propensity to migrate is significantly lower for females. This is usually understood as evidence of more binding family ties for females in contrast to men being more committed to career concerns.[15] As expected, age at Ph.D. is a good predictor of the mobility choice. Compared to the baseline category (being younger than 30), all the coefficients are statistically significant, have a negative sign and their magnitude is increasing in age. In detail, holding all other control variables at their means, the

[13] The table is available upon request.
[14] For instance, differences in pre-migration skill levels can be mirrored in different migration duration.
[15] Faggian et al. (2007) have documented a case in which UK female university graduates are more migratory than men.

probability of temporary migration is 5% lower for individuals aged 30-34 and 10% lower for individuals aged more than 34. Having changed city to attend the Ph.D. increases the probability of subsequent mobility, while the presence of children in the family lower the odds to move abroad. Although not explicitly reported, fields of study turn out to be relatively poor predictors in the migration equation, with the exception of physics and industrial engineering. Finally, note that to account for differences related to granting institutions, province fixed-effects were included in the estimation.

We now examine the results of the earning equation, in which the log of post-move wages was regressed against the indicator of international temporary mobility, individual characteristics, job characteristics, family background, academic background and a full set of origin and destination fixed effects. As discussed in Section 3, we deal with the endogeneity of temporary migration through an endogenous dummy variable model. Thus, the earning equation has been augmented with the hazard rate described in equation 8 and computed after the auxiliary probit regression described in equation 7. Before proceeding, we stress the fact that, despite the estimation protocol tries to account for selection into migration, identification could still be threaten by the possible residual correlation between the length of stay abroad and the error term in the earning equation. Therefore, at this stage, the results might still be biased.

The coefficient of the main variable of interest has a negative sign and is statistically significant. Quantitatively, temporary migration is associated to a reduction in log wages of 0.221, which increases to 0.312 when we also include the (exogenous) number of months spent abroad (column 3). In both regressions (columns 2 and 3 in table 3), we noticed small effects on the estimated coefficients for the other regressors and a positive and highly significant effect on the selection-correction term. Thus, we cannot reject the null hypothesis that the error terms of the migration and employment equation are correlated. Moreover, the result points to positive selection of migrants, suggesting that temporary migrants are a self-selected group whose unobservables characteristics are simultaneously associated with both higher wages and a higher propensity to migrate. This is a novel result in the literature, which favor the hypothesis that the best of the brightest consider the option of further investments in human capital soon after they finish studying.

The last column reports the estimates from the model in which we consider the length of time spent abroad as an additional endogenous regressor. As previously explained, we tackle this problem by first running a probit model from which we recover the inverse Mill's ratio (which corresponds to the first branch in equation 8). Then we regress the length of time spent abroad on the Mill's ratio and other covariates to obtain predicted durations. Finally, we estimate equation 11.

Table A1 (column 2) in the appendix shows the results from the model in which the duration abroad is regressed against the inverse Mill's ratio and a rich set of control variables. As it can be seen from the table, the Mill's ratio turns out to be highly significant and has a positive sign, indicating that individuals with longer spells are a self-selected group among the pool of returnees. Thus, individuals with prolonged length of stay are expected to have a higher earning capacity due to their unobserved traits and put more value on their experience abroad.

Estimated coefficients on other controls suggest that females tend to spend almost 7 months less than males in the temporary destination. As expected, duration also decreases with age and if there are children in the family. Differently, past mobility to attend the Ph.D. is positively associated to duration. Interestingly, while fields of study were poor predictors in the binary migration choice, they are very relevant in predicting the amount of time spent abroad. In particular, we find that doctorates with a Ph.D. in either physics, biology, economics, statistics or social sciences tend to spend more time than graduates from different disciplines.

Turning the attention to the regression of interest, our estimates indicate that there is now a specific reward associated to temporary migration, but only for those individuals who spend no less than 19 months in a foreign country, as each month spent abroad yields a marginal increase in average earnings of 3.28%. Thus, neglecting the importance of the length of time spent abroad would deliver the misleading conclusion that temporary migration is overall a bad investment for high skilled individuals. Instead, the returns are negative only for those individuals who choose to return home early, while the remaining returnees may achieve their goals in terms of skills acquisition in the host country and enjoy higher wages when back to their country of origin. Moreover, prolonged periods of experience abroad may improve individuals' ability to adapt in different types of occupations requiring different knowledge. For instance, in Charlot et al. (2005), the number of abilities increases with the duration of schooling which can be combined in a larger number of ways, yielding better expected performances in the labor market. Instead, those who go back home sooner do not accumulate a sufficiently large amount of skills and abilities. Alternatively, early returnees might be those individuals who mistakenly chosen an international migration path, as in Borjas and Bratsberg (1996).

In terms of policy making, the estimates suggest that policies increasing the incentives to return to the home country may reduce the benefits for those who had otherwise planned longer periods in a host country. By increasing the incentive to return home, such policies might lead individuals to spend less time than they would optimally do, reducing their investments in skills and decreasing individual gains from migration.

6 Robustness and sensitivity

This section presents several robustness and sensitivity checks to validate the results presented so far.

Checking for heterogeneous returns

As recently noted in the program evaluation literature, if the gains from program participation vary according to individuals' characteristics, estimates may suffer from the so called heterogeneous treatment bias (Heckman et al. 2006). To tackle this issue, we allow for a more flexible model by taking into account the possible heterogeneity in treatment response ($\beta^1 \neq \beta^0$) and by relaxing the hypothesis of limited unobserved heterogeneity ($\epsilon^1 \neq \epsilon^0$). In particular, this latter hypothesis let us separately estimate the correlations between each treatment status and wages. Unobserved characteristics may include the set of skills and abilities that contributes to an individual's wage and its propensity to temporarily move abroad, which may be different in the subpopulations of migrants and non-migrants.

The variability in treatment response can be captured in a regression framework with the inclusion of the term $(x - \bar{x})\gamma t$, which is itself endogenous. Formally, we still rely on a Heckman two-step selection model where equation (13) can be reformulated as follows[16]:

$$y_i = \mu_0 + \beta' x_i + t_i(\mu_1 - \mu_0) + t_i \gamma_1 \widehat{temp}_i + t_i \gamma_0'(x_i - \bar{x}) + \\ + \rho_1 \sigma_i t h_i^t + \rho_0 \sigma_i (1 - t) h_i^t + v_i, \quad (14)$$

where ρ_1 and ρ_{10} are the correlations between each treatment status and wages, v is the error term and h^t is the hazard rate in equation 9. We postulate that individuals with higher scientific productivity are more informed about research funding and work experiences abroad and so they are also likely to have greater knowledge of (potential) costs and benefits associated with the choice of temporary migration. Hence, they could ultimately be able to obtain higher wages once they return home. Moreover, younger Ph.D.s may benefit more from mobility because having obtained the Ph.D. while younger is often perceived as a measure of effectiveness and commitment, which in turn can be

[16] See Wooldridge (2010).

rewarded with higher wages in the labor market. At the same time, being younger is also associated with a higher propensity to migrate, thus we let the treatment indicator interact with age at Ph.D. For completeness, we also use gender to capture other dimensions along which the heterogeneous treatment bias could deploy its effect.

Table 4 presents two sets of results which refer, respectively, to the endogenous dummy variable model and the model with endogenous duration. As it can be readily seen, both models do not produce sensible changes in the estimated coefficients of the main regressors and the control variables alike compared with our previous results. Moreover, the coefficients accounting for heterogeneous returns are always statistically insignificant, suggesting that the heterogeneous treatment bias is not relevant in our case. The estimates also confirm the previous finding about the unobserved heterogeneity for temporary migrants and, in addition, suggest that non-migrants are endowed with unobserved traits such that the error component in the treatment status negatively correlates with the error component in the wage equation.

Instrumental variables

To further corroborate the validity of our results, we include two instruments in the selection equations 8 and 11. We searched for valid instruments within the data and in external data sources as well. First, survey respondents were asked to report if during the Ph.D. they had been involved in some form of training abroad for at least one month. Second, we use the (log) rate of unemployment at the NUTS3 level compiled by the Italian National Institute of Statistics.

Previous mobility patterns have been thoroughly used in similar studies as predictors of future mobility.[17] In our case, we use the dummy on foreign training during the Ph.D. as an exclusion restriction. Having spent time abroad during the Ph.D. can in principle be associated with future mobility. During periods abroad, individuals may lower the psychological cost of being mobile, acquire proficiency in a foreign language[18] and increase their knowledge of possible future destinations. Thus, this instrument may contain sufficient information to predict future mobility. Nevertheless, it will be a valid instrument only if periods of training abroad in a student's curriculum can be effectively excluded from the wage regression. From this point of view, we cannot totally rule out the possibility that having undertaken training abroad does not influence subsequent wages.

[17] For instance, Abreu et al. (2015) use migration to attend university and migration after graduation as instruments to post-graduation moves and inter-industry mobility for a sample of UK graduates.
[18] Gibson and McKenzie (2011), for instance, find that students who study a foreign language are more likely to move abroad.

However, we can argue, first, that in most cases, training programs for Ph.D.s are directed to acquire specific skills that might have a high depreciation rate. Since we observe Ph.D.s after three and five years after graduation, the value of those skills probably reduces and, thus, is less related to current wages. Moreover, to the extent that wages are advertised as in models of wage posting, our instrumental variable should not play a critical role in wage determination. For instance, models of directed search as in Moen (1997) or Shimer (2005) typically assume that there is wage posting, and empirical evidence of this mechanism can be found in Hall and Krueger (2010) for the USA and Brenzel et al. (2013) for Germany. In both studies, the authors report that two-thirds of hirings are characterized by wage posting. In addition, since we control for both university fixed effects and the type of degree awarded, we do not expect past mobility to have a direct effect on wages, especially after 3 and 5 years after graduation.

Our second instrument is the (log) rate of unemployment at the NUTS3 level. In particular, we assign to individuals the unemployment rate of the province where the Ph.D. was attended. It turns out that this instrument performs particularly well in the estimation of the length of time spent abroad.

Complete results on the selection equations are presented in table A2 in the appendix, while in table 5 we report the IV results for the main equation with and without heterogeneous effects. The estimates largely confirm our previous results.

Subsamples

To explore the stability of the point estimates discussed so far, we present in table 6 the results carried out on different sub-populations. First, we rerun our estimates on two sub-samples for whom we trim the 5% and 10% of the observations with the highest and lowest probability of return migration. In both cases, results confirm that international temporary migration improve the earning capacity of those who stay abroad for at least one year and that return migrants are a positively self-selected on unobservable traits.

Two further estimates are produced to investigate in more detail the presence of differences related to gender. We find that it takes longer for men to reach a sufficient accumulation of human capital compared to female Ph.D.s. While for women positive returns are predicted after 9 months of experience abroad, men are expected to gain after one year and a half.

We also checked if the results were sensible to public versus private employment, as skill requirements in entry positions might vary substantially between the public and the private sector. It turns out that while in the public sector one year of experience is enough to earn higher wages, individuals in the private sector are on average better off if their experience abroad had been of at least two years. This might reflect the fact that the Ph.D. title is not yet recognized as a plus in the Italian labor market as much as it is worth in other countries with similar education systems.

We finally report estimates carried out on the subsamples of individuals whose Ph.D. was awarded by Universities located in the Centre-North or in the South, as differences in the quality of granting institutions has been a hotly debated topic in recent research. Also in this case the results are in line with the main estimates discussed so far.

7 Conclusions

In order to perform an analysis of the wage effects associated to temporary international migration of individuals placed at the upper tail of the skill distribution, this paper has addressed two critical issues: the endogeneity of the migration decision and the endogeneity of the length of time spent abroad. In doing so, we have exploited a unique dataset compiled by the Italian Institute of Statistics covering the entire population of two cohorts of doctorates who received the degree from an Italian university in 2008 and 2010, respectively. Tackling both issues turned out to be extremely important to determine the actual wage effects ascribable to temporary periods of experience abroad and to provide major indications for policy design.

We have shown that failing to account for both sources of endogeneity would deliver misleading results of expected returns to returning. Indeed, while estimates that takes into account only the selection into migration suggest that temporary migration is a bad investment for high skilled individuals, a different picture emerges when we endogenize also the length of stay abroad. In particular, we have shown that individuals start gaining positive returns only if their experience abroad exceeds around one year and a half. The results are likely to reflect the idea that it takes time to increase the human capital endowment up to a point in which the rewards in the home country exceed those of non-migrants.

In terms of guidance to policy making, our results suggest that policies increasing the incentives to return to the home country with the aim of reducing the brain drain may reduce the benefits for those who had otherwise planned longer periods in a host country. By increasing the incentive to return home, such policies might push individuals to re-emigrate sooner than they would optimally do reducing their investments in skills and decreasing individual gains from migration.

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Table 1: Summary statistics

Variable	All		Migrants		Non-migrants	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Monthly wage (log)	7.311	0.355	7.344	0.317	7.307	0.360
Returnee	0.124	0.330				
Duration	1.580	6.058	12.746	12.405		
IV1: Unemployment rate(log)	2.688	0.503	2.663	0.520	2.691	0.500
IV2: Training abroad during PhD	0.387	0.487	0.607	0.489	0.356	0.479
Change city for PhD	0.329	0.470	0.390	0.488	0.321	0.467
Female	0.537	0.499	0.466	0.499	0.548	0.498
Age at PhD (base: < 30)	0.300	0.458	0.443	0.497	0.279	0.449
Age at PhD (30-34 years)	0.457	0.498	0.450	0.498	0.458	0.498
Age at PhD (>35 years)	0.243	0.429	0.107	0.309	0.262	0.440
Teaching during PhD	0.479	0.500	0.499	0.500	0.476	0.499
Northern University	0.433	0.495	0.432	0.496	0.433	0.495
Scientific productivity						
Journal articles	7.403	9.710	10.894	11.148	6.909	9.385
Patents	0.103	0.585	0.142	0.727	0.098	0.562
PhD on time	0.853	0.354	0.872	0.335	0.851	0.356
PhD required for job	0.479	0.500	0.710	0.454	0.446	0.497
Job access (public competition)	0.617	0.486	0.668	0.471	0.610	0.488
Post-doc contract	0.247	0.431	0.398	0.490	0.225	0.418
Job with teaching	0.547	0.498	0.592	0.492	0.541	0.498
Job with RD	0.729	0.445	0.863	0.344	0.710	0.454
Already working before PhD	0.330	0.470	0.181	0.385	0.351	0.477
Work experience	5.018	2.054	4.353	2.113	5.112	2.029
Job sector (base: Agriculture)	0.018	0.133	0.013	0.111	0.019	0.136
Industry	0.084	0.277	0.070	0.255	0.085	0.280
Services	0.898	0.302	0.917	0.275	0.896	0.306
PhD fields of study						
Math/Computer sciences	0.033	0.179	0.040	0.197	0.032	0.176
Physics	0.042	0.202	0.075	0.264	0.038	0.191
Chemical sciences	0.061	0.240	0.065	0.246	0.061	0.239
Earth science	0.025	0.157	0.018	0.133	0.026	0.160
Life sciences	0.102	0.302	0.118	0.322	0.099	0.299
Medicine	0.157	0.364	0.119	0.325	0.163	0.369
Agriculture and veterinary	0.068	0.252	0.063	0.243	0.069	0.253
Civil Engineering/Architecture	0.059	0.236	0.048	0.213	0.061	0.240

Industrial Engineering and IT	0.130	0.337	0.122	0.328	0.132	0.338
Literary and history	0.087	0.281	0.078	0.269	0.088	0.283
Pedagogy and psychology	0.088	0.284	0.085	0.280	0.089	0.284
Law	0.051	0.220	0.052	0.222	0.051	0.220
Economics and statistics	0.058	0.233	0.068	0.252	0.056	0.231
Political and Social sciences	0.038	0.191	0.048	0.213	0.036	0.187
Others characteristics						
Scientific high school	0.840	0.367	0.857	0.350	0.838	0.369
Bachelor grade: 66-103	0.129	0.335	0.109	0.311	0.132	0.339
Bachelor grade: 104-108	0.130	0.336	0.123	0.329	0.131	0.337
Bachelor grade: 109-110	0.741	0.438	0.768	0.422	0.737	0.440
With children	0.407	0.491	0.268	0.443	0.427	0.495
Mother education (degree)	0.239	0.427	0.288	0.453	0.232	0.422
PhD cohort 2008	0.506	0.500	0.590	0.492	0.494	0.500
Observations	8981		1113		7868	

Table 2: Wages by length of stay abroad

Duration abroad	All			PhD cohort 2008			PhD cohort 2010		
	Obs.	Monthly wage	Std. Dev.	Obs.	monthly wage	Std. Dev.	Obs.	Monthly wage	Std. Dev.
Non-migrants	7868	7.307	0.360	3883	7.327	0.362	3985	7.287	0.358
<= 1 year	789	7.311	0.322	435	7.317	0.334	354	7.302	0.306
1-2 years	169	7.380	0.259	109	7.387	0.226	60	7.368	0.311
2-3 years	94	7.431	0.300	68	7.419	0.320	26	7.464	0.239
=> 4 years	61	7.546	0.329	45	7.542	0.358	16	7.556	0.235

Table 3: Returns to temporary migration

	(1)		(2)		(3)		(4)	
treatment	-0.0290**	(0.0126)	-0.221***	(0.0612)	-0.312***	(0.0622)	-0.586***	(0.106)
treatment intensity	0.00424***	(0.000659)			0.00452***	(0.000658)	0.0323***	(0.00616)
female	-0.0977***	(0.00670)	-0.108***	(0.00705)	-0.109***	(0.00703)	-0.103***	(0.00829)
age at PhD (base: < 30)								
age at PhD (30-34 years)	-0.0259***	(0.00843)	-0.0422***	(0.00927)	-0.0433***	(0.00927)	-0.0348***	(0.0108)
age at PhD (>35 years)	-0.0588***	(0.0137)	-0.0896***	(0.0156)	-0.0932***	(0.0156)	-0.0821***	(0.0182)
teaching during PhD	0.00476	(0.00636)	0.00689	(0.00638)	0.00731	(0.00637)	0.00792	(0.00745)
northern University	0.133***	(0.0383)	0.117***	(0.0383)	0.119***	(0.0383)	0.146***	(0.0449)
Scientific productivity								
journal articles	0.00206***	(0.000358)	0.00208***	(0.00036)	0.00206***	(0.000357)	0.00179***	(0.00042)
Patents	0.0200***	(0.00452)	0.0198***	(0.00454)	0.0197***	(0.00453)	0.0200***	(0.00532)
PhD on time	0.0273***	(0.0105)	0.0265**	(0.0105)	0.0266**	(0.0105)	0.0252**	(0.0123)
PhD required for job	0.0318***	(0.00889)	0.0336***	(0.00890)	0.0325***	(0.00889)	0.0345***	(0.0104)
job access (public competition)	0.136***	(0.0103)	0.133***	(0.0102)	0.135***	(0.0102)	0.134***	(0.0119)
post-doc contract	0.0250***	(0.00920)	0.0263***	(0.00923)	0.0244***	(0.00920)	0.0239**	(0.0108)
job with teaching	-0.00986	(0.00800)	-0.0119	(0.00800)	-0.00962	(0.00800)	-0.0101	(0.00935)
job with RD	0.0927***	(0.00949)	0.0922***	(0.00950)	0.0923***	(0.00948)	0.0923***	(0.0111)
already working before PhD	0.0465***	(0.0122)	0.0501***	(0.0122)	0.0472***	(0.0122)	0.0507***	(0.0142)
experience	0.0301***	(0.00901)	0.0291***	(0.00904)	0.0310***	(0.00900)	0.0285***	(0.0105)
experience (squared)	-0.00227**	(0.00101)	-0.00236**	(0.00101)	-0.00242**	(0.00101)	-0.00229*	(0.00118)
job sector (base: Agriculture)								
Industry	0.258***	(0.0365)	0.253***	(0.0364)	0.256***	(0.0366)	0.249***	(0.0427)
Services	-0.138***	(0.0362)	-0.140***	(0.0361)	-0.138***	(0.0361)	-0.137***	(0.0422)
constant	7.115***	(0.103)	7.186***	(0.105)	7.177***	(0.108)	7.153***	(0.128)
hazard			0.134***	(0.0329)	0.153***	(0.0326)	0.330***	(0.0571)
FE: PhD NACE-3 code	Yes		Yes		Yes		Yes	
FE: work NACE-3 code	Yes		Yes		Yes		Yes	
bachelor graduation year	Yes		Yes		Yes		Yes	
Ateco sectors (2 digits)	Yes		Yes		Yes		Yes	
PhD cohort	Yes		Yes		Yes		Yes	
bachelor grade	Yes		Yes		Yes		Yes	
mother education	Yes		Yes		Yes		Yes	
high school	Yes		Yes		Yes		Yes	
R_sq	0.324		0.323		0.326		0.325	
Observations	8981		8981		8981		8981	

Table 4: Heterogeneous effects

	(1)		(2)	
treatment	-0.272***	(0.0721)	-0.883***	(0.176)
treatment intensity	0.00435***	(0.000667)	0.0656***	(0.0113)
female	-0.116***	(0.00782)	-0.119***	(0.0127)
age at PhD (base: < 30)				
age at PhD (30-34 years)	-0.0482***	(0.0103)	-0.0519***	(0.0168)
age at PhD (>35 years)	-0.108***	(0.0171)	-0.131***	(0.0284)
teaching during PhD	0.00788	(0.00691)	0.0129	(0.0113)
northern University	0.112***	(0.0385)	0.150**	(0.0628)
Scientific productivity				
journal articles	0.00220***	(0.000389)	0.00165**	(0.000641)
Patents	0.0209***	(0.00519)	0.0198**	(0.00844)
PhD on time	0.0265**	(0.0105)	0.0231	(0.0171)
PhD required for job	0.0323***	(0.00888)	0.0348**	(0.0145)
job access (public competition)	0.135***	(0.0102)	0.133***	(0.0166)
post-doc contract	0.0236**	(0.00922)	0.0203	(0.0150)
job with teaching	-0.00963	(0.00800)	-0.00733	(0.0130)
job with RD	0.0918***	(0.00948)	0.0916***	(0.0155)
already working before PhD	0.0459***	(0.0122)	0.0467**	(0.0198)
experience	0.0303***	(0.00901)	0.0260*	(0.0147)
experience (squared)	-0.00234**	(0.00101)	-0.00197	(0.00165)
job sector (base: Agriculture)				
Industry	0.256***	(0.0366)	0.244***	(0.0597)
Services	-0.138***	(0.0362)	-0.136**	(0.0588)
constant	7.209***	(0.112)	7.235***	(0.206)
		heterogeneity		
female	0.0226	(0.0182)	0.0259	(0.0299)
age at PhD (base: < 30)				
age at PhD (30-34 years)	-0.0107	(0.0203)	-0.000156	(0.0334)
age at PhD (>35 years)	0.00298	(0.0407)	-0.00742	(0.0660)
Scientific productivity				
journal articles	-0.000794	(0.000819)	-0.000827	(0.00136)
Patents	-0.00805	(0.00944)	-0.00506	(0.0160)
teaching during PhD	0.00465	(0.0176)	0.00317	(0.0291)
unobs. heterogeneity: non-migrants	-0.258***	(0.0498)	-0.912***	(0.150)
unobs. heterogeneity: migrants	0.113***	(0.0391)	0.417***	(0.0887)
FE: PhD NACE-3 code	Yes		Yes	

FE: work NACE-3 code	Yes	Yes
bachelor graduation year	Yes	Yes
Ateco sectors (2 digits)	Yes	Yes
PhD cohort	Yes	Yes
bachelor grade	Yes	Yes
mother education	Yes	Yes
high school	Yes	Yes
R_sq	0.327	0.33
F statistic (unob. heter.)	14.64	18.81
Observations	8981	8981

Table 5: Instrumental variables

	(1)		(2)	
treatment	-0.524***	(0.0987)	-0.682***	(0.144)
treatment intensity	0.0381***	(0.00612)	0.0610***	(0.0105)
female	-0.0933***	(0.00875)	-0.0989***	(0.0118)
age at PhD (base: < 30)				
age at PhD (30-34 years)	-0.0284**	(0.0113)	-0.0370**	(0.0158)
age at PhD (>35 years)	-0.0616***	(0.0186)	-0.0833***	(0.0252)
teaching during PhD	0.00829	(0.00808)	0.0119	(0.0110)
northern University	0.154***	(0.0469)	0.162***	(0.0591)
Scientific productivity				
journal articles	0.00162***	(0.000465)	0.00160**	(0.000631)
Patents	0.0195***	(0.00607)	0.0207**	(0.00840)
PhD on time	0.0226*	(0.0132)	0.0219	(0.0166)
PhD required for job	0.0359***	(0.0112)	0.0367***	(0.0141)
job access (public competition)	0.130***	(0.0128)	0.130***	(0.0161)
post-doc contract	0.0232**	(0.0118)	0.0206	(0.0148)
job with teaching	-0.00983	(0.00999)	-0.00812	(0.0125)
job with RD	0.0949***	(0.0120)	0.0950***	(0.0150)
already working before PhD	0.0446***	(0.0153)	0.0406**	(0.0193)
experience	0.0285**	(0.0114)	0.0269*	(0.0144)
experience (squared)	-0.00206	(0.00129)	-0.00184	(0.00162)
job sector (base: Agriculture)				
Industry	0.246***	(0.0453)	0.244***	(0.0572)
Services	-0.139***	(0.0442)	-0.139**	(0.0556)
constant	7.111***	(0.128)	7.155***	(0.177)
hazard	0.297***	(0.0535)		
			heterogeneity	
female			0.0213	(0.0293)
age at PhD (base: < 30)				
age at PhD (30-34 years)			0.0072	(0.0315)
age at PhD (>35 years)			0.0135	(0.0587)
Scientific productivity				
journal articles			-0.000721	(0.00135)
Patents			-0.00817	(0.0175)
teaching during PhD			0.00452	(0.0286)
unobs. heterogeneity: non-migrants			-0.626***	(0.122)
unobs. heterogeneity: migrants			0.338***	(0.0733)

FE: PhD NACE-3 code	Yes	Yes
FE: work NACE-3 code	Yes	Yes
bachelor graduation year	Yes	Yes
Ateco sectors (2 digits)	Yes	Yes
PhD cohort	Yes	Yes
bachelor grade	Yes	Yes
mother education	Yes	Yes
high school	Yes	Yes
R_sq	0.33	0.333
F statistic (unob. heter.)		14.19
Observations	8397	8397

Table 6: Sub-populations

sub-samples:	exclusion of extremes: 5%		exclusion of extremes: 10%		female		male		Public sector		Private sector		Northern Universities		Southern Universities	
treatment	-0.510***	(0.121)	-0.598***	(0.152)	-0.354**	(0.146)	-0.602***	(0.132)	-0.414***	(0.0993)	-0.306*	(0.179)	-0.499***	(0.155)	-0.347***	(0.107)
intensity	0.0461***	(0.0087)	0.0497***	(0.0097)	0.0454***	(0.0106)	0.0352***	(0.0072)	0.0339***	(0.0066)	0.0143*	(0.0086)	0.0450***	(0.0108)	0.0206***	(0.0062)
hazard	0.287***	(0.0647)	0.332***	(0.0804)	0.198**	(0.0786)	0.349***	(0.0725)	0.239***	(0.0544)	0.181*	(0.0957)	0.290***	(0.0834)	0.195***	(0.0582)
Obs.	7557		6717		4454		3889		5903		2404		3430		4960	

Table A1: first and second stage

	I stage		II stage	
female	-0.201***	(0.0374)	-6.811***	(1.098)
age at PhD (base: < 30)				
age at PhD (30-34 years)	-0.234***	(0.0410)	-7.885***	(1.249)
age at PhD (>35 years)	-0.616***	(0.0587)	-20.67***	(3.378)
teaching during PhD	0.0528	(0.0358)	1.715***	(0.314)
northern University	-0.232	(0.221)	-8.731***	(1.450)
change city for PhD	0.103***	(0.0374)	3.594***	(0.578)
children	-0.315***	(0.0393)	-10.41***	(1.726)
constant	-0.618**	(0.262)	-41.31***	(8.045)
invmills (II stage)			37.62***	(6.601)
FE: PhD NACE-3 code	Yes		Yes	
PhD fields of study	Yes		Yes	
PhD cohort	Yes		Yes	
bachelor grade	Yes		Yes	
mother education	Yes		Yes	
high school	Yes		Yes	
R_sq	0.071		0.05	
Observations	8981		8981	

Table A2: IV - first and second stage

	I stage		II stage	
IV1: rate of unemployment (log)	0.13	(0.133)	4.332***	(0.673)
IV2: training abroad during PhD	0.499***	(0.0387)	17.12***	(1.921)
female	-0.185***	(0.0393)	-6.398***	(0.725)
age at PhD (base: < 30)				
age at PhD (30-34 years)	-0.215***	(0.0433)	-7.275***	(0.825)
age at PhD (>35 years)	-0.514***	(0.0619)	-17.52***	(2.021)
teaching during PhD	0.0616	(0.0377)	2.003***	(0.270)
northern University	-0.247	(0.228)	-9.378***	(1.182)
change city for PhD	0.0977**	(0.0393)	3.495***	(0.404)
children	-0.311***	(0.0416)	-10.49***	(1.223)
constant	-1.242***	(0.437)	-63.30***	(8.219)
invmills (II stage)			38.36***	(4.696)
FE: PhD NACE-3 code	Yes		Yes	
PhD fields of study	Yes		Yes	
PhD cohort	Yes		Yes	
bachelor grade	Yes		Yes	
mother education	Yes		Yes	
high school	Yes		Yes	
R_sq	0.101		0.0696	
F statistics / chi square (instruments)	167.2		39.71	
Observations	8397		8397	