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Temporary Migration and Wages of Ph.D.s. Stay Longer or Come Back Sooner?

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This paper examines the wage implications of temporary migration for two cohorts of Italian Ph.D.s. Special attention is given to the duration of the international experience, its contribution to earned wages and the selectivity of returnees. Returnees are found to be a self-selected group whose unobservable characteristics are simultaneously associated with both higher wages and a higher propensity to migrate. Moreover, we find positive returns for those who stay longer and negative returns for those who come back sooner. The results are confirmed in several robustness and sensitivity checks.

Keywords: back movers; education; high-skilled migrants; international returnees; selectivity; self-selection; human capital; wage-premia.

JEL Classifications: I23, J3, J61, F22

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 part of an optimal life-cycle planning, individuals move within and across national borders to reach the locations in which skills can be acquired effectively and/or are better rewarded. Such mobility, in turn, plays a crucial role in determining the expansion and contraction of the supply of high-skilled labor for a country. In this context, while college and university graduates have become a reference group in the research on high-skilled migration (Faggian & McCann 2009; Haapanen & Tervo 2011; Corcoran et al. 2010; Venhorst et al. 2011; Groen 2004), we know relatively little about location choices and labor

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market outcomes of individuals holding a Ph.D. Moreover, the literature on graduate migration has so far mainly focused on permanent migration experiences and has largely overlooked equally important episodes of temporary migration. 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 wage of two cohorts of Italian Ph.D.s.

Our focus on doctorate recipients 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 (Grogger & Hanson 2015). Furthermore, Ph.D.s are trained in academic environments opened 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 faced both quantitative and qualitative changes. While in the past decades the worldwide development of higher education systems has yielded a growing number of students receiving a doctorate degree,[1] 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; Gaeta et al. 2022). 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. Occupational mismatch has been proved to have detrimental consequences in terms of both earnings (Gaeta et al. 2023; Cultrera et al. 2023) and job satisfaction levels (Alfano et al. 2021) of Ph.D. holders, especially in fields of studies (such as humanities and social science) for which the opportunities to be employed outside of academia are less evident (Hancock 2023). On the other hand, both internal (Aronica et al. 2023) and international (Ghosh & Grassi 2020) migrations could reduce job mismatch, improve the job satisfaction and boost the wage premia of PhD graduates. At the individual level, mobility allows researchers to access better-equipped institutions, collaborate with leading scholars, and engage in international networks (Passeretta et al., 2018), thereby enhancing their academic reputation, research productivity and their employability both in the public and private sectors. Geographic mobility is a pivotal matter also to characterize the interplay between human capital development and labor market dynamics of Ph.D. holders. For instance, Franzoni et al. (2012) report that four out of ten emigrated scientists from Italy Spain, France, Germany and Switzerland are willing to return to their home country conditional on valid job opportunities. These kinds of mobility are certainly relevant for the Italian labour market where there is a lack of demand for PhDs in the private sector and employment disparities between North and South are particularly marked

[1] 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.

(Parenti et al. 2022). However, this paper is specifically concerned with episodes of return migration. Research highlights how Ph.D. holders returning to their home countries often bring with them advanced skills and international networks, contributing to local academic and industrial ecosystems (Børing et al., 2015). However, this benefit is conditional on the length and quality of their foreign experiences, making it imperative to analyze mobility's impact on both wages and employment outcomes in different contexts.

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 also the importance of return migration as a possible channel through which source countries may benefit from international migration.[2] 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 premium (Reinhold & Thom 2013; de 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 the *scientific* capital stock, reputation or involvement in scientific networks, all of which may facilitate their career in both private and public institutions in the domestic labor market.

All of this suggests that a crucial factor, largely neglected in previous research, is the amount of time individuals choose to spend abroad. Empirical models implemented in the migration literature often dichotomize the choice to stay or come back, but do not consider the length of time spent in other countries. Nevertheless, the theory suggests that observed outcomes in the labor market are likely to reflect human capital investments, which are 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. To the best of our knowledge, this study is the first attempt that sheds light on the relationship between wages of Ph.D. holders and the length of temporary migration.

To sum up, 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 yields 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 needs to be considered as endogenous by practitioners to capture unobserved selectivity among returnees.

[2] Other possible benefits, which are not discussed in this work, are related to remittances. See Docquier and Rapoport (2006), Hatton (2014) and suggested references for further details on the topic.

In detail, this paper is the first documenting positive selection related to the choice of migrating and negative selection related to the length of stay abroad.

The implication of our findings should be evaluated in light of the ongoing academic and policy debate focused on the international competition for talents (Docquier & Machado 2015). 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,[3] aimed at attracting and retaining talents on a global scale (Beine et al. 2008). 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. Our estimates suggest that policies aimed at increasing the incentives to return to the home country may actually reduce the benefits for those who had otherwise planned longer periods in a host country. Such policies might lead individuals to spend less time than they would optimally do, reducing their investment in human capital and, in turn, their gains from migration.

We also wish to acknowledge upfront some caveats 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 cannot 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. Third, we are aware that our analysis focuses exclusively on return migrations that may occur within the short time period between the completion of the PhD and the moment of the interview. Thus, it is important to take into account that the analyzed population of returnees excludes those individuals that may eventually return to Italy in the more distant future. Finally, it is worth noticing the cohorts analyzed in this study crossed significant macroeconomic and institutional challenges. The aftermath of the 2008 financial crisis and subsequent sovereign debt crisis substantially reduced academic employment opportunities and reshaped labor market conditions in Italy. Simultaneously, academic reforms, such as the Gelmini reform, increased precariousness in entry-level academic roles (Passaretta et al., 2018). These contextual elements likely influenced migration decisions and employment outcomes, further underscoring the value of examining short-term return migration within this turbulent period.

[3] 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.

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, respectively, in section 5 and 6. Section 7 concludes.

2 Background

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 thus far contributed to provide the theoretical underpinnings of 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, 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 are shown 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; de 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. The model predicts that the planned

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

duration responds to changes in host and home country wages and that the behavioral response varies depending on 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 distinct migration patterns. Yet, longer spells of temporary migration may also be associated with worse outcomes in the domestic labor market. To the extent that individuals lose 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 (Chiswick & Miller 2009), individuals may accept under-qualified jobs in the home country upon return. In a recent study on graduate (internal) migration, Di Cintio and Grassi (2013) find that individuals choosing to move back home to work (instead of remaining in the area of study) experience a wage loss. The authors point out that while movers obtain a rent because of mobility, back movers choose to give up this rent by returning to the area of origin. Gibson and McKenzie (2012) collect data on five countries experiencing high rates of high-skilled emigration and find that, though migration spurs human capital accumulation, there are negative point estimates in two out of three cases and no significant income gains for the remaining countries.

Empirical evidence on the effects of return migration for internationally 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 earnings 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 increasing with education attainments. [5] 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 additional investments in mobility patterns (Venhorst et al. 2011). In this respect, increasing evidence suggesting positive economic returns to migration has been documented mostly for internal migration patterns of college and university graduates,[6] while few studies have tried to shed light on the international mobility of Ph.D. recipients and their

[5] A summary of further empirical evidence for developing countries can be found in Mayr and Peri (2009).

[6] See, among others, Abreu et al. (2015) and Di Cintio and Grassi (2013).

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 literature has started examining the mobility of doctorate holders. In particular, it has been shown how the propensity to migrate abroad 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 with the international temporary migration of doctoral holders.

3 Research methods

To examine the implications of international temporary migration on wages, we set up an empirical framework in which (log) monthly 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 is a scalar, β 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 is the error term. 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 assume that all that matters for wages is whether any experience abroad has been done. Thus, when we neglect the effect of the length of stay abroad, 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 a random group of individuals. Thus, in the absence of an exogenous source of variation of the incentive to migrate, the binary indicator of mobility is 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).[7] To tackle this problem, we implement an endogenous binary treatment version of Heckman's (1976; 1979) two-step model,[8] 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:

$$t_i^* = \alpha' z_i + e_i \tag{5}$$

and

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

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 wages. Thus, we control for selection in a mincerian-type regression by estimating a selection rule 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 from:

$$Pr(t_i = 1|z_i) = \Phi(\alpha' z_i) \tag{7}$$

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

[7] 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 statistics are given in section 4.

[8] An alternative approach would be to model the migration decision in a multinomial context and correct for selectivity 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 model that is still able to account for selectivity.

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

where ϕ and Φ are, respectively, the probability and cumulative density functions, so that the first branch of eq. 8 represents the inverse Mill's ratio. The estimates are then obtained by augmenting equation (3) 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 equation and the selection equation, 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, which 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 previously discussed, individuals are likely to differ in their marginal costs and benefits of migration in a way that led them to opt for different length of stay abroad.[9] Migration duration is then a potential explanatory factor of the gains/losses experienced after re-migration. In other words, the treatment is not only parametrized as a binary variable, but it deploys its effects on wages also along the length of international experience. Thus, the next step is to consider the possible relationship between wages and the duration of stay abroad. Similarly to Greene (1995) and Terza (1998), we implement a two-step protocol in which the estimated probability to migrate (eq. 7) is used to recover the inverse Mill's ratio ($m_i = \phi(\widehat{\alpha'} z_i)/\Phi(\widehat{\alpha'} z_i)$), which is then used to obtain the selection-corrected estimates (with and without exclusion restrictions) of the length of stay abroad, $\widehat{temp}_i$. Given that the variable *temp* counts the number of months spent in a foreign country, and given the large number of zeros in the data, we use a Negative Binomial model. By augmenting the wage equation in (9) with the predicted duration of stay abroad, we estimate $(\mu_1 - \mu_0)$ and γ:

$$y_i = \mu_0 + \beta' x_i + t_i(\mu_1 - \mu_0) + t_i\gamma\widehat{temp}_i + \rho\sigma_i h_i^t + u_i\,. \quad (10)$$

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

[9] Angrist and Imbens (1995) raise a similar concern when researchers ignore the years-of-schooling variable in estimating the impact of college attendance on earnings.

4 Data description

The empirical analysis uses data from the second Professional Integration Survey of Ph.D.s (*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 having 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 (or temporary) 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 from the analysis permanent migrants. In this way, we focus exclusively on the Italian job market. As already noted in the introduction, we acknowledge that individuals who permanently migrated abroad (1,519 observations) may return at a later stage. As these cases are beyond the scope of this analysis, they have been dropped from our sample. We also drop observations with missing information on important variables used in our analysis such as wages (5,753 observations of which 1,231 observations refer to unemployed individuals) or other job characteristics (69 observations). The resulting size of the dataset on which we perform our empirical analysis is 8,981 observations.

[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.

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.[12] Return migrants represent around 12.4% of the selected population and have accumulated, on average, about 12 months of experience abroad and they also show higher wages with respect to non-migrants. Interestingly, the sub-populations of returnees and stayers differ along several 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 is a small gender differences in the average time spent abroad, as male returnees stay only one month more in a foreign country.[13]

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.[14] Neglecting the duration of temporary international experience, rough unconditional figures reveal that migrants earn around 3.7% more than non-migrants.[15]

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[12] The descriptive statistics refer to the subsample used in the analysis, where the subpopulation of permanent migrants (1519 observations) have been dropped from our sample.

[13] It could be highlighted that the female subpopulation with respect to both mobile and non-migrants does not change significantly if individuals still abroad are included in the analysis. As a matter of fact, if we consider both temporary and permanent migrants, the full sample would include the 51,7% of female Ph.D. At the same time, it could be noted that, among the female migrants, the 46,3% have been opted for a temporary against a permanent migration. Differently, the share of female over the mobile population would amount to 42,6%. These figures confirm that, overall, males tend to be more mobile than females and, potentially, women might prefer permanent migration to mitigate gender discrimination in their country of origin. We thank an anonymous referee for suggesting this point.

[14] 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.

[15] The percentages have been computed on wage levels rather than logs.

Table 1: Summary statistics

Variable	All		Return-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
Return-migrants	0.124	0.330				
Duration (# of months)	1.580	6.058	12.746	12.405		
IV1: Training abroad during PhD	0.387	0.487	0.607	0.489	0.356	0.479
IV2: Unemployment rate (log)	2.688	0.503	2.663	0.520	2.691	0.500
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 (>34 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
PhD in time	0.853	0.354	0.872	0.335	0.851	0.356
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
Job characteristics						
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

Table 1 continued

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
Other characteristics						
Scientific/Grammar 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	

Moreover, 61.7% of Ph.D.s have access to the labor market through a public competition, but only a small fraction holds a post-doc position (24.7%). As far as job sectors are concerned, around 90% of Ph.D.s works in services. Finally, returnees have lower job experience compared to stayers, and it is less likely that they were working at the time of their degree. Table 1 also reports other personal characteristics and the distribution of graduates among 14 fields of study.

Table 2: Wages by length of stay abroad

	All			PhD cohort 2008			PhD cohort 2010		
	Obs.	**Monthly wage (log)**	**Std. Dev.**	**Obs.**	**Monthly wage (log)**	**Std. Dev.**	**Obs.**	**Monthly wage (log)**	**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

However, if we compare average individual monthly wages computed at different length of stay, the picture is different. Table 2 above 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, durations between one and two years are associated with a 7.5% higher wage, durations between two and three years with a 13.2% increase and durations of at least four years with a 27%increase. In the rest of the paper, we attempt to assess to what extent this pattern mirrors a causal link between duration abroad and domestic earnings.

Since the econometric models illustrated in section 3 are made up of different stages, we first illustrate the variables included in the auxiliary equations used to predict both the migration decision and duration, then we discuss the control variables included in the wage equation. In particular, notice that, except for indicators of past mobility and fields of study, all the controls in the auxiliary equations are also included in the wage equation.

We consider the decision to return to depend on personal and demographic characteristics - such as gender, the presence of children in the family and mother education. Also, we control for having attended scientific/grammar high school, bachelor grade, age at Ph.D. and teaching duties during the Ph.D. to account for students' commitment, ambition and motivation. Since there is a large consensus suggesting that previous migration experiences are correlated with subsequent spatial mobility, attitude toward mobility is proxied by a dummy equal to one if graduates had changed city to attend the Ph.D. As further controls, we include cohort indicators, a dummy for having attended the Ph.D. in northern Universities, dummies for fields of study and province-specific intercepts. With the exception of a very few provinces,[16] each province usually hosts only one university. Thus, our province fixed effects should also capture differences in the academia of origin.

[16] Italian provinces correspond to the NUTS 3 classification.

As far as the wage equation is concerned, the set of control variables is richer, as we add, compared to the aforementioned equations, also many job-related variables. In particular, we control for years of job experience (both with a linear and quadratic term) and we include variables that indicate if individuals carry out R&D and/or teaching activities in their job, if they hold a post-doc position, if they had access the job through a public competition, in which economic sector (industry, services and agriculture) they are employed. In addition, since the survey delivers information related to the scientific productivity in terms of published articles and patents, we are able to partially account for ability in conducting research. Moreover, we proxy determination and motivation using a dummy equal to one whenever students graduated on time and we also consider whether they were already working at the time of their degree. Lastly, we add fixed effects for 53 provinces in which the degree was awarded, 110 work provinces and 22 industry intercepts to control for differences in economic activities.

Given the large number of explanatory variables, we check the degree of multi- collinearity with the variance inflation factor (VIF). In detail, the square root of the VIF indicates how much larger the standard error is, compared to what it would have been if that variable was uncorrelated with the other independent variables. In our analysis, all of the VIFs are lower than 10 (many are lower than 2) and the mean VIF is 1.64. Thus, since all of the VIFs are relatively low, we can be confident that multicollinearity is not an issue in our analysis.

5 Estimation results

OLS estimates of the relationship between log monthly wages and temporary migration are presented in the first column of table 3. The main regressors of interest are the dummy for the migration experience and the number of months spent abroad. Both are treated as exogenous variables. Being a return migrant is associated with lower wages, but the effect is mitigated by the positive coefficient on the duration. In particular, only those who stay abroad for more than 6.8 months tend to enjoy a wage gain. While we only report the estimates with the full set of control variables, in more parsimonious specifications of the empirical model[17] 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

[17] The table is available upon request.

problem of the dichotomous variable alone.[18] We thus expect differences between the estimates of the endogenous dummy variable model and the estimates of the model in which we endogenize also the migration duration.

Table 3: Returns to temporary migration

	OLS		**Endogenous dummy variable model**		**Endogenous dummy variable model**		**Endogenous duration**	
	(1)		**(2)**		**(3)**		**(4)**	
Return-migrants	-0.029**	(0.013)	-0.221***	(0.061)	-0.312***	(0.062)	-0.397***	(0.085)
Duration (# of months)	0.004***	(0.001)			0.005***	(0.001)	0.016***	(0.004)
Female	-0.098***	(0.007)	-0.108***	(0.007)	-0.109***	(0.007)	-0.105***	(0.007)
Age at PhD (base: < 30)								
Age at PhD (30-34 years)	-0.026***	(0.008)	-0.042***	(0.009)	-0.043***	(0.009)	-0.041***	(0.010)
Age at PhD (>34 years)	-0.059***	(0.014)	-0.090***	(0.016)	-0.093***	(0.016)	-0.086***	(0.016)
Teaching during PhD	0.005	(0.006)	0.007	(0.006)	0.007	(0.006)	0.008	(0.007)
Northern University	0.133***	(0.038)	0.117***	(0.038)	0.119***	(0.038)	0.131***	(0.040)
PhD in time	0.027***	(0.010)	0.027**	(0.011)	0.027**	(0.010)	0.026**	(0.011)
Scientific productivity								
Journal articles	0.002***	(0.000)	0.002***	(0.000)	0.002***	(0.000)	0.002***	(0.000)
Patents	0.020***	(0.005)	0.020***	(0.005)	0.020***	(0.005)	0.020***	(0.005)
Job characteristics								
PhD required for job	0.032***	(0.009)	0.034***	(0.009)	0.032***	(0.009)	0.034***	(0.009)
Job access (public competition)	0.136***	(0.010)	0.133***	(0.010)	0.135***	(0.010)	0.134***	(0.011)
Post-doc contract	0.025***	(0.009)	0.026***	(0.009)	0.024***	(0.009)	0.025***	(0.010)
Job with teaching	-0.01	(0.008)	-0.012	(0.008)	-0.01	(0.008)	-0.011	(0.008)
Job with RD	0.093***	(0.009)	0.092***	(0.010)	0.092***	(0.009)	0.092***	(0.010)
Already working before PhD	0.046***	(0.012)	0.050***	(0.012)	0.047***	(0.012)	0.051***	(0.013)
Work experience	0.030***	(0.009)	0.029***	(0.009)	0.031***	(0.009)	0.029***	(0.009)
Work experience (squared)	-0.002**	(0.001)	-0.002**	(0.001)	-0.002**	(0.001)	-0.002**	(0.001)
Job sector (base: Agriculture)								
Industry	0.258***	(0.037)	0.253***	(0.036)	0.256***	(0.037)	0.251***	(0.038)
Services	-0.138***	(0.036)	-0.140***	(0.036)	-0.138***	(0.036)	-0.138***	(0.037)
constant	7.115***	(0.103)	7.186***	(0.105)	7.177***	(0.108)	7.172***	(0.113)
hazard			0.134***	(0.0329)	0.153***	(0.033)	0.228***	(0.046)

[18] For instance, differences in pre-migration skill levels can be mirrored in different migration duration.

Table 3 continued

	OLS		Endogenous dummy variable model		Endogenous dummy variable model		Endogenous duration	
FE: PhD NUTS-3 code	Yes		Yes		Yes		Yes	
FE: work NUTS-3 code	Yes		Yes		Yes		Yes	
bachelor graduation year	Yes		Yes		Yes		Yes	
Industry FE	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		0.324	
Observations	8981		8981		8981		8981	

Notes: The dependent variable is the log monthly wage. ***, **, * denote, respectively, significance levels at 1, 5 and 10 %. Corrected standard errors are in parenthesis.

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 10% less than males[19]. 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. in 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) where, initially, we neglect the effect of the length of stay abroad. In particular, in the first stage, we estimate a selection rule (i.e. the migration equation) that predicts the probability to be a return migrant, and then we proceed to the analysis of the earning equation augmented by the hazard rate. Results of the first stage are presented in table A1, column 1, in the Appendix. 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

[19] If the dummy switches from 0 to 1, the percentage impact on Y is equal to $100[exp(\hat{\beta}) - 1]$.

career concerns.[20] 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 probability of temporary migration is 4% lower for individuals aged 30-34 and 9% 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, the set of dummies capturing the impact of the fields of study turn out to be a relatively poor predictor in the migration equation, with the exception of physics and industrial engineering. Finally, note that to account for differences related to Ph.D. granting institutions, province fixed-effects were included in the estimation.

We now examine the results of the earning equation, in which the log wage is regressed against the binary 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 first stage probit regression described in equation (7).

By neglecting the length of experience abroad, results in table 3, column 2, confirm the negative relationship between log wages and temporary migration. However, before proceeding, we stress the fact that, despite the estimation protocol tries to account for selection into migration, identification could still be threatened by the possible residual correlation between the length of stay abroad and the error term in the earning equation. Therefore, since the results might still be biased and individuals are likely to differ in the length of stay abroad, we try to capture also the effect of the migration duration on wages.

In table 3, column 3, the coefficient of the main variable of interest has still a negative sign and is statistically significant. Quantitatively, temporary migration is associated with a reduction in log wages of 0.221, which increases to 0.312 when we also include the (exogenous) number of months spent abroad. By comparing 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

[20] In a study on UK university graduates, Faggian et al. (2007) have documented a case in which females are more migratory than their male counterparts.

associated with both higher wages and a higher propensity to migrate. Although the debate on migrants selectivity is still controversial, several empirical studies have found evidence consistent with the positive selection of more general groups of migrants (Belot & Hatton 2012; Grogger & Hanson 2011; Chiquiar & Hanson 2005). Our result corroborates such literature by first documenting positive selection for Ph.D. migrants. Moreover, this result is aligned with the hypothesis tested in Gibson and McKenzie (2012) that the best of the brightest consider the option of further investments in human capital soon after they finish studying.

The last column of table 3 reports the estimates of the model in which we also account for the endogeneity of the length of time spent abroad. As previously explained, we tackle this problem by first running a probit model (as in the first stage reported in table A1, column 1, in the Appendix) from which we recover the inverse Mill's ratio (which corresponds to the first branch in equation 8). Then, we use a negative binomial model to regress the length of time spent abroad on the inverse Mill's ratio and other covariates to obtain the selection-corrected estimates of the length of stay abroad. Finally, we estimate equation (10) where the expected impact of temporary migration on wages depends also on the duration of stay and the estimates control for both sources of endogeneity.

Table A1 (column 2) in the appendix shows the results of the second stage. The inverse Mill's ratio turns out to be highly significant, indicating that returnees are a self-selected group among the pool of Ph.D.s. Moreover, we find a negative coefficient, meaning that unobservable traits that lower individuals' earning capacity are also related to prolonged lengths of stay. If we interpret the selection mechanism as determined by ability traits, negative selection implies that less able Ph.D.s tend to stay longer abroad to acquire more skills in the host country and, then, enjoy higher wages when back to their country of origin. At the same time, the negative selection with respect to the length of time spent abroad may signal some difficulties in adapting to foreign contexts. Thus, individuals with less ability to adapt to unfamiliar contexts would tend to spend shorter periods abroad.

Estimated coefficients on other controls suggest that females tend to remain abroad longer than males, probably to counter-balance gender discrimination in the home country. This is in line with findings in Alfano *et al.* (2021) where the authors suggest that a gender gap in hourly wages exists among Ph.D. holders, with sizeable differences by sector of employment and field of specialization.

Given the selection mechanism, duration increases with age and if there are children in the family. Differently, past mobility to attend the Ph.D. is negatively associated with duration, as well as the regressor referred to teaching activities during the Ph.D. Even if not explicitly reported, 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 those with a Ph.D. in either physics, chemical sciences, psychology, law, economics and statistics or social sciences tend to remain abroad shorter periods than graduates from different disciplines.

Turning the attention to the wage equation, our estimates (table 3, column 4) do not produce sensible changes in the estimated coefficients of the control variables compared with our previous results.[21] However, as it can be readily seen, results on the main regressors indicate that there is now a specific reward associated to temporary migration, but only for those individuals who spend no less than 24 months in a foreign country, as each month spent abroad yields a marginal increase in average monthly earnings of 1.61%. This result is partly in line with previous empirical evidence of a wage premium for return migrants, as in Barrett and O'Connell (2010) and Ambrosini et al. (2015). At the same time, we refine previous evidence by documenting the wage penalty suffered by early returnees. In our data, 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.

To some extent, our empirical results can be reconciled with theoretical models of temporary migration. From one side, the negative wage effect associated with shorter periods abroad may reflect the outcome of the early returnees who mistakenly chose an international migration path, as in Borjas and Bratsberg (1996). On the other side, the association between prolonged periods of experience abroad and higher wages in the origin country is in support of models that explain return migration as a decision that responds to where human capital can be acquired more effectively, and where the return to human capital is highest (Dustmann et al. 2011).

Alternatively, protracted lengths of stay may be associated with a process of skill diversification and, thus, to an improvement of individuals' ability to adapt to different types of occupations requiring different knowledge. For instance, in Charlot et al. (2005), the number of individual skills increases with the duration of schooling, yielding better expected performances in the labor market. Instead, those who go back home sooner do not accumulate a sufficiently differentiated amount of skills and abilities, resulting in poorer performances in the domestic labour market.

Our estimates also deliver novel policy prescriptions. Policies aimed at 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. For instance, in Dustmann (2011), return migration can mitigate the welfare loss of the brain drain to the extent that

[21] As the F statistic on the joint significance of the industry dummies is equal to 37.66, differences in economic activities are also particularly relevant. Complete tables are available upon request.

returnees actually augment local skills. Thus, decision makers should calibrate public interventions by taking into account the length of time migrants have already spent in a host country.

5 Robustness and sensitivity

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

5.1 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[22].

The variability in treatment response can be captured in a regression framework with the inclusion of the term $(x - \overline{x})\gamma t$, which is itself endogenous. Formally, we still rely on a two-step selection model where equation (10) can be reformulated as follows[23]:

$$y_i = \mu_0 + \beta' x_i + t_i(\mu_1 - \mu_0) + t_i\gamma_1\widehat{temp}_i + t_i\gamma_0'(x_i - \bar{x}) +$$

$$+\rho_1\sigma_i t h_i^t + \rho_0\sigma_i(1-t)h_i^t + v_i, \qquad (11)$$

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 (8). 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 rewarded with higher wages in the labor

[22] For instance, Alfano et al. (2022) document the high heterogeneity even among highly skilled Italian migrants.

[23] See Wooldridge (2010).

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 (column 1) and the model with endogenous duration (column 2). Both models tackle treatment heterogeneity. 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 previous findings on unobserved heterogeneity.

Table 4: Returns to temporary migration - Heterogeneous effects

	Endogenous dummy variable model		**Endogenous duration**	
	(1)		**(2)**	
Return-migrants	-0.272***	(0.0721)	-0.516***	(0.110)
Duration (# of months)	0.00435***	(0.000667)	0.0328***	(0.00640)
Female	-0.116***	(0.00782)	-0.118***	(0.00920)
Age at PhD (base: < 30)				
Age at PhD (30-34 years)	-0.0482***	(0.0103)	-0.0550***	(0.0123)
Age at PhD (>34 years)	-0.108***	(0.0171)	-0.121***	(0.0204)
Teaching during PhD	0.00788	(0.00691)	0.0123	(0.00821)
Northern University	0.112***	(0.0385)	0.128***	(0.0453)
PhD in time	0.0265**	(0.0105)	0.0253**	(0.0124)
Scientific productivity				
Journal articles	0.00220***	(0.000389)	0.00191***	(0.000461)
Patents	0.0209***	(0.00519)	0.0205***	(0.00611)
Job characteristics				
PhD required for job	0.0323***	(0.00888)	0.0342***	(0.0105)
Job access (public competition)	0.135***	(0.0102)	0.134***	(0.0120)
Post-doc contract	0.0236**	(0.00922)	0.0233**	(0.0109)
Job with teaching	-0.00963	(0.00800)	-0.00952	(0.00941)
Job with RD	0.0918***	(0.00948)	0.0916***	(0.0112)
Already working before PhD	0.0459***	(0.0122)	0.0480***	(0.0143)
Work experience	0.0303***	(0.00901)	0.0271**	(0.0106)
Work experience (squared)	-0.00234**	(0.00101)	-0.00212*	(0.00119)

Table 4 continued

	Endogenous dummy variable model		Endogenous duration	
	(1)		(2)	
Industry	0.256***	(0.0366)	0.250***	(0.0431)
Services	-0.138***	(0.0362)	-0.138***	(0.0425)
constant	7.209***	(0.112)	7.236***	(0.143)
female	0.0226	(0.0182)	0.0246	(0.0216)
age at PhD (base: < 30)				
age at PhD (30-34 years)	-0.0107	(0.0203)	-0.00511	(0.0241)
age at PhD (>34 years)	0.00298	(0.0407)	0.00248	(0.0481)
teaching during PhD	0.00465	(0.0176)	0.00366	(0.0210)
Scientific productivity				
journal articles	-0.000794	(0.000819)	-0.000865	(0.000983)
Patents	-0.00805	(0.00944)	-0.00709	(0.0115)
unobs. heterogeneity: non-migrants	-0.258***	(0.0498)	-0.589***	(0.0943)
unobs. heterogeneity: migrants	0.113***	(0.0391)	0.243***	(0.0567)
FE: PhD NUTS-3 code	Yes		Yes	
FE: work NUTS-3 code	Yes		Yes	
bachelor graduation year	Yes		Yes	
Industry FE	Yes		Yes	
PhD cohort	Yes		Yes	
bachelor grade	Yes		Yes	
mother education	Yes		Yes	
high school	Yes		Yes	
R_sq	0.327		0.326	
F statistic (unob. heter.)	14.64		19.77	
Observations	8981		8981	

Notes: The dependent variable is the log monthly wage. ***, **, * denote, respectively, significance levels at 1, 5 and 10 %. Corrected standard errors are in parenthesis

6 Instrumental variables

To further corroborate the validity of our results, we include two instruments to predict the migration duration. 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 number of patents granted by the European Patent Office disaggregated at the NUTS-3 level.

Previous mobility patterns have been thoroughly used in similar studies as predictors of future mobility.[24] 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 foreign languages[25], and increase their knowledge of possible future destinations. On the other hand, past mobility could help individuals to evaluate and judge their aptitude to adapt to the culture and context of a foreign country. Those who have already experienced mobility abroad may have developed practical adaptation skills, understanding different social norms, and managing new or unexpected situations. Moreover, exposure to foreign cultures allows individuals to develop competencies such as cultural empathy, mental flexibility, and the ability to understand different perspectives. These skills are crucial for effective adaptation to a new context. Also, past experiences can reveal personal strengths and areas for improvement, helping individuals recognize their learning and adaptation styles, as well as potential challenges they might face in the future. Successfully facing and overcoming challenges related to past mobility strengthens confidence in one's ability to live in a new cultural environment. 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 can argue, first, that in most cases, training programs for Ph.D.s are directed to acquire specific skills that might have a certain 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. Second, 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

[24] 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.

[25] Gibson and McKenzie (2011), for instance, find that students who study a foreign language are more likely to move abroad.

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 number of patents, which we assign to individuals according to the province where the Ph.D. was attended. We believe this instrument may capture differences among geographic areas in terms of innovation propensity of both firms and academic institutions. These areas should be able to better absorb high skilled labor employable in R&D departments. At the same time, the more local economies are innovative, the higher is the incentive for individuals to temporarily move abroad to increase their scientific capital stock and become more employable upon return.

Results on the migration duration are presented in table A2 in the appendix, while in table 5 we report the IV results for the wage equation both with and without heterogeneous effects.

Table A2 in the appendix reveals that our instruments are highly significant and positively affect the length of time spent abroad. A joint test of significance for the instruments reveals a statistic higher than 166, which largely exceeds the threshold of 10 suggested by Stock and Yogo (2005). Overall, the signs and the significance of the other regressors are the same as in the first and second stage estimates, as already described in Section 5.

Finally, the estimates in table 5 largely confirm our previous results as wage gains are detected only for those individuals who do not choose to return home early. This result supports 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. Moreover, when we look at the heterogeneous response to treatment (table 5, column 2), again we do not find evidence of individual heterogeneity in the response of wages to temporary migration.

Table 5: Returns to temporary migration - Instrumental variables

	Without heterogeneity		**With heterogeneity**	
	(1)		**(2)**	
Return-migrants	-0.345***	(0.069)	-0.327***	(0.078)
Duration (# of months)	0.010***	(0.002)	0.013***	(0.002)
Female	-0.107***	(0.007)	-0.118***	(0.008)
Age at PhD (base: < 30)				
Age at PhD (30-34 years)	-0.040***	(0.009)	-0.050***	(0.011)
Age at PhD (>35 years)	-0.088***	(0.016)	-0.113***	(0.017)
Teaching during PhD	0.008	(0.006)	0.009	(0.007)
Northern University	0.126***	(0.039)	0.117***	(0.039)
PhD in time	0.027**	(0.011)	0.026**	(0.011)

Table 5 continued

	Without heterogeneity		With heterogeneity	
	(1)		(2)	
Journal articles	0.002***	(0.000)	0.002***	(0.000)
Patents	0.020***	(0.005)	0.020***	(0.005)
Job characteristics				
PhD required for job	0.033***	(0.009)	0.033***	(0.009)
Job access (public competition)	0.134***	(0.010)	0.134***	(0.010)
Post-doc contract	0.026***	(0.009)	0.025***	(0.009)
Job with teaching	-0.012	(0.008)	-0.012	(0.008)
Job with RD	0.092***	(0.010)	0.092***	(0.010)
Already working before PhD	0.051***	(0.012)	0.049***	(0.012)
Work experience	0.028***	(0.009)	0.027***	(0.009)
Work experience (squared)	-0.002**	(0.001)	-0.002**	(0.001)
Job sector (base: Agriculture)				
Industry	0.255***	(0.037)	0.256***	(0.037)
Services	-0.136***	(0.037)	-0.136***	(0.037)
constant	7.173***	(0.106)	7.223***	(0.113)
hazard	0.199***	(0.037)		
			Heterogeneity	
female			0.025	(0.019)
age at PhD (base: < 30)			-0.008	(0.021)
age at PhD (30-34 years)			0.005	(0.042)
age at PhD (>35 years)			-0.001	(0.001)
teaching during PhD			-0.007	(0.010)
Scientific productivity			0.004	(0.018)
journal articles			0.025	(0.019)
Patents			-0.008	(0.021)
unobs. heterogeneity: non-migrants			-0.394***	(0.058)
unobs. heterogeneity: migrants			0.155***	(0.042)
FE: PhD NUTS-3 code	Yes		Yes	
FE: work NUTS-3 code	Yes		Yes	
bachelor graduation year	Yes		Yes	
Industry FE	Yes		Yes	

	Without heterogeneity		With heterogeneity	
	(1)		(2)	
PhD cohort	Yes		Yes	
bachelor grade	Yes		Yes	
mother education	Yes		Yes	
high school	Yes		Yes	
R_sq	0.328		0.329	
F statistic (unob. heter.)			9.124	
Observations	8981		8981	

Notes: The dependent variable is the log monthly wage. ***, **, * denote, respectively, significance levels at 1, 5 and 10 %. Corrected standard errors are in parenthesis.

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 by Italian Ph.D. graduates. 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 endogeneity issues turned out to be extremely important to determine the actual wage effects caused by 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 take 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 temporary migrants start gaining positive returns only if their experience abroad exceeds around 24 months. 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 incentive 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 return sooner than they would optimally do, reducing their investments in skills and decreasing individual gains from

migration. Thus, policies should be calibrated to avoid suboptimal human capital investments. Obviously, since high-achievers in the education system are only part of the high-skilled migrant population, our results should be extended with caution to the whole category of skilled returnees. Nonetheless, due to the importance of Ph.D. holders in the creation and diffusion of scientific knowledge on a global scale, we believe future research should strengthen our understanding on their migration patterns and labor market outcomes.

Future research could delve into whether the findings of this paper vary based on gender or field of doctoral specialization, offering a more nuanced understanding of return migration and its effects. Exploring gender-specific dynamics might reveal distinct patterns in how male and female Ph.D. experience and benefit from returning to their home countries. Similarly, investigating differences across fields of study could shed light on the ways academic background and different job market opportunities affect the results. Moreover, a deeper approach, examining the interplay between gender and field of specialization, could provide richer insights into the combined effects of these factors. Additionally, longitudinal studies could assess how these outcomes change over time, offering a dynamic perspective on their long-term impact. By considering these dimensions, future research could also inform policy recommendations tailored to address the needs of returning doctoral graduates more effectively. This expanded perspective would not only refine theoretical frameworks but also guide practical interventions aimed at maximizing the benefits of return migration for individuals and societies alike.

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Appendix

Table A1: Migration decision and migration duration

	I stage Migration decision		**II stage Migration duration**	
	(1)		**(2)**	
female	-0.201***	(0.037)	1.569**	(0.612)
age at PhD (base: < 30)				
age at PhD (30-34 years)	-0.234***	(0.041)	1.916***	(0.698)
age at PhD (>34 years)	-0.616***	(0.059)	4.951***	(1.899)
teaching during PhD	0.053	(0.036)	-0.486***	(0.185)
northern University	-0.232	(0.221)	1.161	(0.872)
change city for PhD	0.103***	(0.037)	-0.754**	(0.319)
children	-0.315***	(0.039)	2.622***	(0.957)
constant	-0.618**	(0.262)	16.701***	(4.606)
invmills (II stage)			-12.146***	(3.744)
FE: PhD NUTS-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			
Observations	8981		8981	

Notes: At the first stage, the dependent variable is the binary indicator of temporary mobility. At the second stage, the dependent variable is the number of months spent abroad. ***, **, * denote, respectively, significance levels at 1, 5 and 10 %. Standard errors in the II stage (in parenthesis) are corrected for the two-stage procedure.

Table A2: IV migration duration

IV1: training abroad during PhD	1.025***	(0.082)
IV2: number of patents (NUTS-3)	0.010***	(0.003)
female	1.420**	(0.622)
age at PhD (base: < 30)		
age at PhD (30-34 years)	1.694**	(0.705)
age at PhD (>35 years)	4.516**	(1.917)
teaching during PhD	-0.437**	(0.191)
northern University	0.822	(0.838)
change city for PhD	-0.685**	(0.322)
children	2.335**	(0.967)
constant	10.955**	(4.992)
invmills (II stage)	-11.005***	(3.783)
FE: PhD NUTS-3 code	Yes	
PhD fields of study	Yes	
PhD cohort	Yes	
bachelor grade	Yes	
mother education	Yes	
high school	Yes	
Chi-square (instruments)	166.86***	
Observations	8981	

Notes: The dependent variable is the number of months spent abroad. ***, **, * denote, respectively, significance levels at 1, 5 and 10 %. Standard errors (in parenthesis) are corrected for the two-stage procedure.