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Migration flows by educational attainment: Disentangling the heterogeneous role of push and pull factors

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Abstract

This paper analyzes the determining factors of South to Center-North migration flows in Italy for five different educational groups. We find strong support for the paramount role of *total* and *education-specific* migration networks. Furthermore we unveil an inverse relationship between the magnitude of the response of migration flows by educational level and the regional endowment of human capital. More generally, it emerges that once migrants educational attainment is explicitly considered, the reaction of migration flows is highly heterogeneous with respect to the push and pull factors that usually determine them. In the economics of migration literature, these results have not yet been documented.

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1. INTRODUCTION

We conduct an empirical investigation of bilateral migration flows disaggregated by migrants educational (skill) level from eight southern Italian regions, which are the least economically developed, towards twelve center-northern Italian regions, those being the most economically advanced.

There is a historical divide in Italy between these two macro-areas of the country. Such a wide difference, which is not only economic but also social, cultural and political in nature, harks back to when Italy was split into different political entities. When it became a unified state in 1861, many differences were still present across the territories that then became part of the unified nation.[1] More recently, after World War II, a phenomenon of internal mass migration took place: millions of individuals moved from the southern to the center-northern regions looking for better jobs and, in general, better living conditions. Pugliese (2002) reported that starting from 1951, over about a quarter of a century 3.7 million Southerners migrated to the center-northern regions. Piras & Melis (2007) provided similar results with 3.8 million individuals moving from the South to the Center-North during the period from 1971 to 2002. A recent report from Svimez (2015) highlighted that between 2001 and 2014, 1.7 million individuals left the southern regions and headed to the Center-North. These mass migration flows gave rise to large migrant communities (internal diasporas) of Southerners in the center-northern regions.

The first important novelty of this paper is the investigation into the role of migration networks at the internal level for Italy, in conjunction with the human capital of migrants. While at the international level the key role of migration networks has been established in several empirical works (see, *inter alia*, Munshi, 2016; Beine, Docquier & Özden, 2015; Beine, Docquier & Özden, 2011); quite surprisingly at the internal level, empirical contributions rooted in an economic framework are rare.[2] As for Italy, various authors have

investigated internal migration flows in the last decade (see *inter alia* Piras, 2017, 2012; Etzo, 2011); however, only one paper has studied the impact of migrants networks on *total* migration flows (Piras, 2020), the results of which proved that migration networks have been at work also at the internal level for Italy. In the present study, given the focus on migration flows by educational level, we further extend the analysis on the role of internal migration networks by investigating them in two dimensions: *total* migration networks and *education-specific* migration networks. It should be noted that very few studies have dealt with the potentially differentiated role of networks based on their level of education (Beine & Salomone, 2013; Beine, Noel & Ragot, 2014) and, to the best of our knowledge, no one has yet tackled the issue of the differential impact of migrants networks based on educational level migration flows, when divided into more than two levels of education.

The second novelty of relevance, is the in-depth analysis of the role of regional human capital on migration flows by *educational level*. In the case of Italy, previous studies have shown that the average level of regional human capital influences *total* interregional migration flows, although its role has not yet been fully understood. During the period from 1970 to 2005, for the whole sample of Italian regions and without taking migrants networks into account, Piras (2017) showed that for *total* migration flows, human capital at the destination had no role in shaping migration, whereas at the origin, it worked as a restraining factor. In Piras' (2020) study, the role of human capital for *total* migration flows is analyzed in conjunction with the role of *total* migration networks for the period 1980–2013. When looking at South to Center-North migration flows, human capital at origin takes a positive and statistically significant coefficient equal to 0.81, whereas at destination, it is statistically insignificant. Yet, neither of these two studies investigate migration by disaggregating the flows into five educational levels as we do in this paper, nor do they disentangle migration networks based on the educational levels of previous migrants. To give an idea of how

different the estimated coefficients are when the migrant skill level is considered, in one of our preferred estimates we find that human capital at origin has a negative elasticity of −1.55 for graduate migration flows that becomes positive and equal to 5.49 for migration flows without formal schooling. At destination, human capital has a negative estimated elasticity of −5.42 for graduate migration flows and 6.72 for migration flows of individuals without formal schooling.

To implement our empirical investigation, a unique data set has been assembled for the period 1980–2013 with gross migration flows disaggregated by migrants educational (skill) level, i.e. migrants human capital. In doing so, and this is the third novelty of the paper, we are also able to separately estimate the impact of the other traditional variables (per capita GDP, unemployment and population) used to explain bilateral migration flows. In fact, push and pull factors are likely to differ depending on migrants educational level; hence, empirical analyses that do not account for these differences could deduce misleading results concerning the role exerted by the variables driving migration flows. Once the migrants skill level is explicitly considered, we show that the reaction of migration flows is highly heterogeneous for those variables that traditionally explain them. Thus, the disentanglement of migrants educational level provides a novel context in which to evaluate the role of migration determinants.

One of the main limitations in studying the multifaceted aspects of international migration is the lack of appropriate data. Such a problem is less severe at the intranational level, especially for those countries that record detailed data on internal migration. Since 1970, the Italian National Institute of Statistics (ISTAT) has collected data on interregional migration flows by education level from the municipal registrars offices. The data is then aggregated at the regional level and reported on origin–destination matrices. The five educational levels for which we have been able to gather data are graduates (corresponding to

ISCED 8, 7, and 6 of the UNESCO (2015) classification), upper-secondary school (ISCED 5, 4, and 3); lower-secondary school (ISCED 2); primary school (ISCED 1), and no schooling (ISCED 0).

The rest of the paper is laid out in the following manner: the next section presents the estimation framework upon which we base our empirical investigation. Section 3 illustrates some estimation issues. A discussion of the explanatory variables used in the empirical models and of the relevant literature is held in Section 4. A short description of the data is made in Section 5, whereas the empirical results are shown in Section 6. Section 7 offers a deeper analysis regarding the role of per capita GDP and human capital, and Section 8 focuses on migration networks. Finally, the main findings are summarized in Section 9.

2. MICRO-FOUNDED MODELS OF MIGRATION AND ESTIMATION STRATEGY

A detailed description of the theoretical micro-founded models of migration upon which we based our empirical analysis goes beyond the scope of the present paper. For a comprehensive discussion, the interested reader is referred to the synthesis given by Beine Bertoli & Fernández-Huertas Moraga (2016) and to the original works of Ortega & Peri (2013) and Anderson (2011). Here it is sufficient to say that they are based on the well-known random utility model (RUM). A common and very important characteristic is that these models are purposely designed to cope with the issue of multilateral resistance to migration. As illustrated by Bertoli & Fernández-Huertas Moraga (2013), in the context of migration, multilateral resistance could emerge because the decision to migrate between two countries (or regions inside a country) depends not only on the attractiveness of a given destination but also on the (time-varying) attractiveness of all of the other potential destination countries. In the case of internal migration in Italy for example, if an individual from Calabria in the South

of Italy is considering migrating to Lombardia in the North, the economic factors in other Italian regions (and also other non-economic factors affecting the migration decision) are as important as those in Lombardia. If these factors are not properly accounted for, estimates of the determining factors that affect the decision to migrate will be biased.

Expressed in (log)linear terms, the general empirical specification used to study bilateral migration flows from origin region i to destination region j at time t (m_{ijt}) can be written as follows:

$$m_{ijt} = \boldsymbol{\alpha}'_{\mathbf{i}}\,\mathbf{X_{it}} + \boldsymbol{\gamma}'_{\mathbf{j}}\mathbf{X_{jt}} + \boldsymbol{\varphi}'_{\mathbf{ij}}\mathbf{X_{ijt}} + \varepsilon_{\mathrm{ijt}}\,, \qquad (1)$$

where $\mathbf{X_{it}}$ is the vector of time-varying origin-specific (monadic) variables, $\mathbf{X_{jt}}$ is the vector of time-varying destination-specific (monadic) variables, and $\mathbf{X_{ijt}}$ is the vector of origin–destination-specific (dyadic) time-varying variables, whereas $\boldsymbol{\alpha}'_{\mathbf{i}}$, $\boldsymbol{\gamma}'_{\mathbf{j}}$, and $\boldsymbol{\varphi}'_{\mathbf{ij}}$ are vectors of parameters to be estimated. The structure of the error term $\varepsilon_{\mathrm{ijt}}$ in Equation (1) is decisive in reflecting and capturing the underlying theoretical assumption of the different models. Two simple approaches used to estimate Equation (1) are the two-ways (2-FE) and the three-ways (3-FE) fixed effects error structure. In the 2-FE approach, the error structure is assumed to be $\varepsilon_{\mathrm{ijt}} = \lambda_{\mathrm{t}} + \nu_{\mathrm{ij}} + \mu_{\mathrm{ijt}}$, whereas in the 3-FE approach, it is $\varepsilon_{\mathrm{ijt}} = \lambda_{\mathrm{t}} + \varsigma_{\mathrm{i}} + \varsigma_{\mathrm{j}} + \mu_{\mathrm{ijt}}$, where λ_{t} are time dummies, ς_{i} are origin dummies, ς_{j} are destination dummies, ν_{ij} are origin–destination dummies, and μ_{ijt} is a well-behaved error term. Bertoli and Fernández-Huertas Moraga (2013) pointed out that these approaches are not specifically designed to cope with multilateral resistance to migration, however from the perspective of applied research, their accomplishments should be judged based on their performances in empirical analysis. Coherent with their theoretical model, Ortega & Peri (2013) proposed two empirical specifications. The first specification (termed Ortega–Peri(a) in this paper) includes origin-year (ϑ_{it}) and destination (ς_{j}) dummies, so that the error term can be written as $\varepsilon_{\mathrm{ijt}} = \vartheta_{\mathrm{it}} +$

$\varsigma_j + \mu_{ijt}$. The second specification (Ortega–Peri(b)) adds to the first origin–destination dummies, and the error term becomes $\varepsilon_{ijt} = \vartheta_{it} + \nu_{ij} + \mu_{ijt}$. This is a very demanding specification since all time-invariant bilateral variables are absorbed by fixed effects and cannot be estimated. In the structural gravity model of Anderson (2011), inward and outward multilateral resistance to migration are accounted for, both origin-year and destination-year dummies (θ_{jt}) are included, and the error term becomes $\varepsilon_{ijt} = \vartheta_{it} + \theta_{jt} + \nu_{ij} + \mu_{ijt}$.[3]

Overall, the gravity model of migration can be estimated using various estimation methods. According to Beine et al. (2016), the alternative that best fits the data remains to be empirically identified, with the minimum requirement, for the estimates to be coherent with the RUM model, that regression residuals should not be plagued by cross-sectional dependence (CD). This is the reason why in the empirical section we check for residuals CD by using the test illustrated by Pesaran (2015).[4] We will show that in almost all regressions, the use of a rich set of fixed effects contributes to eliminating, or at least alleviating, such a problem. Hence, they conform quite well to the RUM model upon which the estimates are based.

3. SOME ESTIMATION ISSUES

Some technical issues are briefly discussed before estimating models, the first being endogeneity. Regarding endogeneity caused by reverse causality, we follow the standard practice followed by almost all of the empirical studies in the field (see, *inter alia*, Piras, 2017; Ortega & Peri, 2013; Mayda, 2010; Pedersen, Pytlikova & Smith, 2008) and lag the independent variables by one year. As for endogeneity problems due to omitted variables, the inclusion of an ample set of dummy variables greatly contributes to alleviating these issues. Unfortunately, the contemporaneous inclusion of origin-year and destination-year dummies renders estimated coefficients of the time-varying origin-specific and destination-specific

variables infeasible. To tackle this issue, we use the two-step procedure as described by Head & Mayer (2014) and applied in the empirical trade literature. In migration literature, Özden, Packard & Wagner (2017) and Piras (2020) recently applied this procedure, which firstly consists of regressing migration flows on a set of origin-year, destination-year, and origin–destination dummy variables. In the second step, the estimated origin-year and destination-year fixed effects are regressed on the origin-specific and destination-specific time-varying variables to recover, respectively, the outward (at origin) and the inward (at destination) effects of these variables on bilateral migration flows.

4. EXPLANATORY VARIABLES AND LINKS WITH THE RELEVANT LITERATURE

Equation (1) needs to be operationalized in terms of explanatory variables to be considered at the origin and destination of migration flows. In this regard, the economic literature on migration unanimously considers economic incentives to be the main drivers of decisions to migrate. Per capita GDP and unemployment rates are the most frequently used proxies of the expected income that migrants consider when making their decisions. Per capita GDP at origin (destination) is expected to restrain (attract) migration flows, whereas the unemployment rate is expected to act in the opposite direction. Population, as the mass variable, is also normally included and the expected impact is positive at both origin and destination. In addition, we include the regional level of human capital proxied by the average number of years of schooling of the resident population. We acknowledge that this proxy does not account for all of the multifaceted aspects of human capital, such as the quality of schooling which undoubtedly differs at the international level across countries and which might be different also at the sub-national level. Unfortunately, to the best of our

knowledge and for the time period under investigation, annual regional data on the quality of schooling does not exist.

Human capital has been found to yield mixed results in the empirical literature on migration, which in our opinion depends on several different issues. Firstly, human capital can be defined as "the stock of productive skills, talents, health, and expertise of the labor force" (Goldin, 2016, p. 82) and, in this way, should be measured. The difficulties in measuring human capital, however, are well-known, and researchers are forced to use a kind of proxy that is deemed able to capture the essence of human capital. A human capital proxy, as a minimum requirement, should be a stock variable (the average years of schooling is the most commonly used) and not a flow variable that would represent an investment in human capital. Yet, in many empirical works (see, *inter alia*, Royuela & Ordóñez, 2018, Ruyssen & Rayp, 2014; Pedersen et al., 2008), other proxies (enrollment rates, population shares of a particular educational level, illiteracy rates) are instead used. This creates a tension between the theoretical definition of human capital and its empirical counterpart. A second issue is not specific to human capital, since it is a common concern regarding all variables employed in the context of empirical migration literature. However, when referred to human capital, it helps to explain why this variable frequently shows mixed results. As stated in Section 2, micro-founded models of migration yield a gravity-like equation; explanatory variables should therefore be included in the estimates separately at origin and destination. Though they could legitimately reflect other theoretical models or particular research questions, other ways to implement the analysis do not adhere to the abovementioned micro-founded models and cannot separately identify the strength of the push and pull factors affecting regional migration flows.

Having said that, the role played by regional human capital at origin and destination is not univocal. Theoretical contributions of Borjas (2014, 1991) support the hypothesis that

migration is higher (lower) when the mean level of education in the source (destination) country is higher. In the empirical studies, this happens because the standard practice of using per capita GDP as a proxy for wages (the variable that correctly captures income opportunities for the potential migrants) introduces a distortion in what a potential migrant would actually obtain, since per capita GDP also depends on the rate of returns of all the other production factors and on the endowments of each factor (Clark, Hatton & Williamson, 2007; Mayda, 2010). Hence, a higher per capita GDP at destination does not necessarily imply that a migrant would obtain it, since a higher per capita GDP might be due to a higher per capita capital or higher level of average human capital (Piras, 2017; Ruyssen & Rayp, 2014; Hatton & Williamson, 2010; Mayda, 2010). On the other hand, models in the spirit of the new economic geography (Krugman, 1991) predict a different role for human capital if agglomeration forces, led by economies of scale, attract individuals and firms to a core region. In such a situation, a circular self-reinforcing process of concentration of human capital could occur, so that a core region that already has a high level of human capital attracts human capital, whereas a peripheral region loses human capital.

In our empirical analysis in which migrants are endowed with different levels of human capital, things are even more complex since it is very likely that the impact of regional human capital at origin and at destination will be quantitatively different—or even opposite in sign—depending on the specific migrants level of education. Borjas (1987) can help clarify how migration flows disaggregated by skill level are expected to react to the average level of human capital. Building on Roy's (1951) model, Borjas (1987) showed that if the returns-to-skills are higher at destination rather than at origin (the earnings skill profile at destination is steeper than that at origin), then those individuals above the skill level that corresponds to the average skill (proxied by the average regional human capital) will migrate, whereas those below that level will not migrate. Conversely, if returns-to-skills are lower at destination (the

earnings skill profile at origin is steeper than that at destination), then those individuals below the skill level that corresponds to the average skill will migrate, while those above that skill level will not migrate.

Lastly, and very importantly, we introduce two migration network variables. The first (*education-specific* stock of migrants) is calculated as the stock of migrants with educational level *h* (*h*=graduates, upper-secondary school, lower-secondary school, primary school and no schooling) coming from the region of origin *i* and living in the region of destination *j*. The second is the *total* stock of migrants.[5] Theoretical models (Beine et al. 2015; Beine et al. 2011; Grogger & Hanson, 2011; McKenzie & Rapoport, 2010) and empirical evidence (McKenzie & Rapoport, 2010; Bertoli, 2010) that highlight a potentially differentiated impact of migrants networks for low-skilled in relation to high-skilled migrants exist. Given that one of the main roles played by migrants networks is to reduce migration costs, and since these costs are normally higher for the low-skilled because they face higher assimilation costs, it is expected empirically that the estimated coefficient for the migration network variables is higher for the less-skilled migrants with respect to those highly-skilled. Furthermore, the high-skilled migration flows are likely to be more sensitive to the stock of skilled migrants rather than to the *total* stock of migrants. Conversely, the less-skilled migrants are likely to be more sensitive to the *total* stock of migrants rather than to the *education-specific* stock of migrants (Beine et al., 2014; Beine & Salomone, 2013).

5. DATA DESCRIPTION AND CONSTRUCTION OF THE NETWORK VARIABLES

5.1 Data description

The data set contains 34 years, 8 origin regions and 12 destination regions for a total of 96 bilateral flows, and 3,264 observations. It has been collected mainly from the Italian National

Institute for Statistics (see TABLE A1 in Appendix A for data sources and TABLES A2–A4 for summary statistics of all variables).[6] Zero flows are 84 (2.5% of the sample) for graduate migrants, 23 (0.7%) for upper-secondary school migration flows, 15 (0.5%) for lower-secondary school migration flows, 74 (2.3%) for primary school migration flows, and 272 (8.3%) for migration flows of individuals without formal schooling. Given the logarithmic transformation of all variables, we have set these zero flows to one so as to maintain all data points. In the empirical literature, depending also on the specific case under scrutiny, various solutions have been employed to deal with the occurrence of zeroes in the dependent variable. Some studies simply discard zero flows or add a small positive constant (not necessarily one) to all observations, whereas others apply a transformation of the data, such as the inverse hyperbolic sine transformation, or use some ad-hoc imputation technique. Therefore, this issue seems not to have reached a commonly accepted solution that could be used in all situations. In our analysis, except for primary school migration flows, the occurrence of zeros is very rare across all educational groups, and a specific compelling way of treating them does not seem to be imperative. Nevertheless, as a check of robustness, Appendix B presents the results of the Poisson Pseudo-Maximum Likelihood (PPML) estimator proposed by Santos Silva & Tenreyro (2015, 2006), which, among other desirable statistical properties, is explicitly designed to cope with the presence of zeroes. As shown in TABLE A1, on average, graduate migration flows are 113, upper-secondary school flows 295, lower-secondary school flows 332, primary school flows 201, and no schooling flows 141. However, these figures do not provide much information on the heterogeneous phenomenon since there are huge variations across years, origin–destination pairs, and the educational level of migrants.

[TABLE 1 about here]

TABLE 1 reports the first ten corridors of region-pairs for the five educational groups under scrutiny. For graduate migration flows, we notice that the two most populous southern regions (Campania and Sicilia) appear nine out of ten times as a source region, whereas the two most populous Center-Northern regions (Lombardia and Lazio) always appear as the two main destination regions. In the case of upper-secondary school migrants, the region-pair is always Campania–Lazio. Similarly, for primary school and no schooling migration flows, the region-pairs that appear in the first ten positions are mainly Campania–Lazio and Sicilia–Lombardia. It is also worth highlighting that the first ten positions for graduate and upper-secondary school migration flows are always recorded after 2000, whereas for primary school and no schooling migration flows, the highest flows are recorded before that year. Lower-secondary school migration flows stand in between, which comes as no surprise if one considers that on the one hand during the period under investigation, the overall level of education increased; whilst on the other, those individuals who are better educated are also the most willing to move. FIGURE 1 shows the evolution of the composition of South to Center-North migration flows. At the beginning of the period, half of the migration flows had no schooling or had only primary school education, slightly more than a quarter (27%) had lower-secondary school education, whereas migrants with upper-secondary school education and graduate flows had a share, respectively, of 17% and 6%. In 2012[7], the composition of migration flows was completely different: 25% were graduates, 38% had upper-secondary school education, 28% had lower-secondary school education, and only 8% and 1%, respectively, had primary school education and no education.

[FIGURE 1 about here]

5.2 The networks variables

The stock of education-specific networks of migrants with educational level h (stk_{ijt}^{h}) is calculated as follows:[8]

$$stk_{ijt}^{h} = stk_{ijt-1}^{h} + inflow_{ijt}^{h} - d_{ijt}^{h}\, stk_{ijt-1}^{h} = inflow_{ijt}^{h} + \left(1 - d_{ijt}^{h}\right) stk_{ijt-1}^{h},$$

where $inflow_{ijt}^{h}$ are gross flows of immigrants from origin region *i* to destination region *j* at time *t* and $d_{ijt}^{h} \equiv \left(em_{jit}^{h} + mor_{jt}\right)$ is a depreciation factor that accounts for regional mortality rates (mor_{jt}) and regional emigration rates by educational level (em_{jit}^{h}). To recover the initial stock of migrants, namely stk_{ij1980}^{h}, we assume the following:

$$stk_{ij1980}^{h} = inflow_{ij1980}^{h} + \left(1 - d_{ij1979}^{h}\right) \sum_{t=1970}^{1979} inflow_{ijt}^{h}$$

and approximate the regional stock of immigrants in 1979 by summing up all previously available flows and correcting them by considering the depreciation factor in 1979. Two possible sources of bias in the computation of these stock variables should be highlighted. The first is that we can compute regional emigration rates by educational level but, since we do not have data to compute regional mortality rates by educational level, we are forced to use regional mortality rates for the total population. This approximation does not bias the depreciation factor in a relevant way as long as regional mortality rates are similar across educational levels. Secondly, it could occur that an individual who moves from region *i* to region *j* could, later in his/her lifetime, move again to region *l*. In such a situation, he/she first enters the migration stock of region *i*'s individuals living in region *j* and then into the migration stock of region *j*'s individuals living in region *l*. With our data, unfortunately, we cannot keep track of these multiple changes of residence.

6. EMPIRICAL MODEL

This section delivers a detailed comment on the regression results separately for the five educational levels. We present and discuss the results of the 2-FE and Ortega–Peri(b) models that demonstrate to have better explanatory power in terms of both the overall statistical significance of estimated parameters and residual tests diagnostics. Results for the 3-FE, Ortega-Peri(a), and Anderson models are shown in TABLES B1–B5 in Appendix B.[9] The dependent and all of the independent variables are expressed in logs; hence, the estimated coefficients represent elasticities. Furthermore, the CD test for weak cross-sectional dependence does not reject the null hypothesis for all educational levels but only for graduates and for individuals without schooling in the Ortega-Peri (b) model. This suggests that the results conform quite well to the RUM model upon which the estimates are based. In what follows, we refrain from further commenting upon it.

[TABLE 2 about here]

6.1 Graduates

TABLE 2 reports the estimates regarding graduates. Looking at the estimated coefficients, which in most cases turn out to be statistically significant, some regularities emerge. Let us begin by discussing the role of monadic variables at origin (Panel A) and then those at destination (Panel B). Firstly, contrary to what is theoretically expected, per capita GDP is strongly positively associated with graduate migration flows with estimated coefficients that vary between 1.15 in column (1) and 1.48 in column (2). Secondly, the unemployment rate turns out to be statistically significant (only marginally at 10% of statistical confidence in column (2)) around 0.15/0.17. Thirdly, population has a strong impact on graduate migration flows with an estimated elasticity of 2.18 in the 2-FE and of 2.15 in the Ortega-Peri(b) model. Finally, human capital is always negatively associated with

graduate migration flows and has an estimated elasticity of −1.27 in column (1) and −1.55 in column (2).

Variables at destination exert a strong effect on graduate migration flows. Per capita GDP is very robustly positively associated with graduate migration flows with estimated coefficients equal to 1.50 in both models. The unemployment rate shows a weak (positive) statistically significant relationship with graduate migration flows only in the 2-FE regressions with an estimated elasticity of 0.14. As for population, it confirms its principal role as a pull factor, even stronger than that exerted as a pull factor at origin. Human capital has a statistically very robust and quantitatively high impact: the estimated elasticity is always higher than 5, in absolute value. Finally, the migrants network elasticity is statistically very significant and the coefficient varies from 0.56 in column (1) and 0.46 in column (2).

[TABLE 3 about here]

6.2 Upper-secondary school

TABLE 3 presents the results for upper-secondary school migrants. Estimates reveal that variables at origin have a lower explicative power with respect to those at destination. Among the former, only human capital exerts a clear negative role in both regressions: elasticity varies from −0.71 column (1) to −1.20 in column (2). Besides that, only a negative role for per capita GDP is detected in column (1).

The results are far different when we look at the determinants at destination (Panel B). In this case, the signs of all variables conform to expectations, and are all statistically significant. In more detail, per capita GDP drives migration flows with a very similar estimated elasticity: 0.55 in the 2-FE regressions, and 0.53 in the Ortega–Peri(b) model. Unemployment rate and population are always highly statistically significant: the former

shows a stable (−0.19/−0.20) coefficient, the latter has a very high estimated elasticity: 2.52 in column (1) up to 2.90 in column (2). As for human capital, its negative impact is strongly statistically significant and the estimated elasticity is −2.11 in column (1) and −1.93 in column (2). Lastly, the migrants stock variable is also very important. The sensitivity of migration flows is lower in the Ortega–Peri(b) model (0.45) with respect to the 2-FE model (0.58).

[TABLE 4 about here]

6.3 Lower-secondary school

Empirical estimates for lower-secondary school migration flows are reported in TABLE 4. As regards the role of monadic variables measured at origin (Panel A), we see that per capita GDP and unemployment rate stand out as the main determining factors. Both are always highly statistically significant and report the expected theoretical sign in the range between −1.09/−1.15 in the former, and 0.30/0.28 in the latter. Conversely, population and human capital do not exert any role.[10]

Let us now focus on monadic variables at destination as shown in Panel B. In all estimates, the variables are statistically significant (almost always up to 1%) and conform to the theoretical expectations. As regards per capita GDP, the estimated elasticity is basically the same for the 2-FE and the Ortega–Peri(b) models, around 1.08/1.09. Unemployment rate plays a role as a stay-away factor, which is quantitatively similar to the role played at origin as a pull factor: its elasticity lies around −0.24/−0.25. Population attracts lower-secondary school migration with estimated elasticities of 2.51 in the 2-FE estimate up to 2.77 in the Ortega–Peri(b) model. As far as human capital is concerned, the sign of the estimated coefficients is negative and statistically significant in both regressions: −1.90 in the 2-FE

model and -1.71 in the Ortega–Peri(b) model. Additionally, the presence of migrants networks is a strong predictor of migration flows with an estimated elasticity of 0.75 in column (1) 0.66 in column (2).

[TABLE 5 about here]

6.4 Primary school

TABLE 5 shows the results for migration flows of individuals with primary school level education. Among the explicative variables measured at origin, per capita GDP and human capital are always highly statistically significant. The former has an estimated elasticity of −1.58 in column (1) and −1.21 in column (2), the latter has an even larger range and varies between 3.98 in column (1) down to 1.41 in column (2). The unemployment rate is barely significant in column (1) with an estimated coefficient of 0.12 and significant at 5% in column (2) with a similar point estimate of 0.15. Population operates as a restraining factor for migration flow but is statistically significant al 10% only in the 2-FE models with an estimate of −1.91.

At destination, contrary to theoretical expectations, we find negative estimated coefficients for per capita GDP which turn out to be statistically significant only for the 2-FE model. Conversely, the unemployment rate is correctly signed and statistically significant, with an estimated coefficient of −0.46 in both estimates. As far as population is concerned, the coefficient is statistically significant and equal to 1.57 in the 2-FE specification and 1.41 in the Ortega-Peri(b) model. As for human capital, it is always statistically significant, and the magnitude of the elasticity is very high and stable at around 3.00. Estimates regarding the migrants networks variable reveal that its role is quantitatively higher for the Ortega–Peri(b) model (0.64) rather than for the 2-FE specification (0.57).

[TABLE 6 about here]

6.5 No schooling

The results of migration flows of individuals with no schooling are provided in TABLE 6. Among the variables at origin, only human capital is always highly statistically significant and with a very high estimated coefficient in both regressions (7.52 in column (1) and 5.49 in column (2)). Conversely, per capita GDP is never statistically significant: the unemployment rate is significant only at 10%, whereas population exerts a negative role (operating as a restraining, rather than a pulling, factor) in the 2-FE model but it is not statistically significant in the Ortega–Peri(b) model.

At destination, per capita GDP has a strong negative effect with an estimated elasticity of -2.22 and -1.89 in columns (1) and (2), respectively. The unemployment rate is statistically significant and has the expected negative coefficient equal to −0.58 in both models. Population is barely statistically significant only in column (1). Finally, human capital, as it occurs at origin, exerts a strong positive role in attracting migrants without formal schooling. Analogously to the previous results, we find that migrants networks have a high explicative power also for migration flows of people with no schooling. We observe that the network variable is statistically significant with an estimated elasticity of 0.73 in column (1) and 0.53 in column (2).

7. A DEEPER ANALYSIS OF THE RESULTS REGARDING PER CAPITA GDP AND HUMAN CAPITAL

In this section, we focus on the role of per capita GDP and regional human capital, in order to better understand why the reaction of migration flows by educational attainment is so heterogeneous with respect to these two variables.

7.1 Per capita GDP and human capital at origin

Per capita GDP is the variable that appears most consistently linked with migration flows for all educational levels with a magnitude that appears to be inversely related to the educational level of migrants. In addition, while it operates as a "stay home" factor for migration flows below the graduate level, on the contrary, it acts as a push factor for those most skilled. While noticing that in some circumstances this could happen—for example, if income levels at origin are very low and individuals cannot afford migration costs—in the case of Italian graduate migrants, we deem this not to be the case.[11] In our opinion, this result should be interpreted together with the negative role of regional human capital for graduate migrants at origin and with the fact that returns-to-skills for the highly skilled individuals in the southern regions are higher than those in the center-northern regions (Cingano & Cipollone, 2009). Using a Mincerian approach, Cingano & Cipollone (2009) estimated the returns-to-skills at macro-area level for the South, Center, North-East, and North-West for the period 1987–2000. Their estimates show that while on average returns-to-skills are lower in the South than the Center-North, the returns-to-skills for graduates and holders of upper-secondary education are on the contrary higher in the South vis-à-vis the Center-North. In more detail, returns-to-skills for graduates and upper-secondary education holders equal 8.31 and 6.15, respectively in the South. In the Center they are 7.33 and 5.33, in the North-East 6.97 and 5.28, and finally, in the North-West, they equal 6.76 and 5.87. As discussed in Section 4, based on Borjas (1987) it is expected that when the earnings skill profile at destination is steeper than that at origin, namely the returns-to-skills are higher at destination

than at origin, then those individuals above the average skill level will move. On the contrary, when the earnings skill profile at origin is steeper than that at destination, returns-to-skills are lower at destination, and those individuals below the average skill level will move. The results of Cingano & Cipollone (2009) are perfectly coherent with what we have found here regarding the reaction of graduate and upper-secondary school migration flows according to the Borjas' (1987) model. As shown in TABLES 2 and 3, for graduate and upper-secondary school migration flows, human capital at origin (the South of Italy) displays a negative (restraining) role on migration flows. Conversely, the results presented in TABLES 5 and 6 for the low-skilled (primary school migrants) and the unskilled (no schooling) reveal that regional human capital at origin is positively related with migration flows. Distinctively, a negative relationship between the magnitude of the response of migration flows by educational level and human capital at origin clearly emerges: the higher the educational level of migration flows, the lower (possibly negative) the reaction of these flows to the average human capital at origin is. At the same time, a positive link can be detected between the magnitude of the response of migration flows by educational level and per capita GDP at origin: the higher the educational level of migration flows, the higher (possibly positive) the reaction of these flows is to per capita GDP.

7.2 Per capita GDP and human capital at destination

We observe that per capita GDP at destination always has a positive role as a pull factor for graduate, upper- and lower-secondary migration flows. On the contrary, per capita GDP acts as a stay-away factor at the lower end of the educational level (particularly for migrants with no formal schooling). As regards human capital, its inverse relationship with the sensitiveness of migration flows by educational attainment is confirmed also at destination, and analogously with what was previously seen for these two variables at origin, this result

should be read in light of Borjas' (1987) model and the fact that the returns-to-skills for graduates and holders of upper-secondary education are higher in the southern regions with respect to the center-northern ones.

8. MIGRANTS NETWORKS

In Section 6, we have estimated the determining factors of migration flows by educational attainment by inserting the education-specific migration network variable into the regressions. In this section, firstly, as a robustness check, we present the estimates of the Ortega–Peri(b) model in which total migration networks, along with education-specific migration networks, are also considered inside the regressions.[12] Secondly, we summarize the results concerning the role of migrants networks that we have obtained and link them to the existing literature.

[TABLE 7 about here]

Compared with the corresponding estimate reported in column (2) of TABLE 2, the results in column (1) of TABLE 7 for graduate migration flows clearly show that what really matters is the education-specific network of migrants—the estimated elasticity (0.45) is highly statistically significant—rather than the total migrant networks which turns out to be insignificant. On the contrary, migration flows of individuals with lower-secondary school education and without formal schooling, as reported in columns (3) and (5) of TABLE 7, are positively attracted by total migrants networks alone, with estimated elasticities of 0.59 and 1.43, respectively. Primary school flows, shown in columns (4), display an opposite role of total migrants networks (2.03) with respect to education-specific migrants networks (-0.90).

Finally, for upper-secondary school migration flows (column (2) of TABLE 7), both network variables are statistically significant and exert a positive effect, but the education-specific stock of migrants exerts a stronger role (0.31) when compared with the total stock of migrants (0.25). The different roles of the two migrants networks variables is clearly established: the impact of the total stock of migrants decreases as the migrants skill level increases; conversely, the higher the migrants skill level is, the higher the impact of the education-specific migrants stock.

The results concerning the role of migration networks obtained in this section and Section 6 are summarized below.

Firstly, it is apparent that migration networks have a key role in explaining migration flows by educational level in all estimated models. This is a common result in the literature concerning international migration (Beine et al., 2011; Beine, 2016) that has also recently been documented for total migration flows at the internal level in Italy (Piras, 2020).

Secondly, for graduate and upper-secondary school flows, the sensitivity is higher for education-specific migration networks rather than for total migration networks. Finally, for all other migration flows, we find strong empirical evidence that they are mainly affected by total migration networks.

Beine et al. (2014) investigated similar issues and showed that the elasticity of migration flows is higher for what they called the skilled diaspora (migrants stocks with post-secondary education). Indeed, they found that students in higher education benefit the most from those students with higher education who are already settled in the destination country with respect to the total diaspora. Beine & Salomone (2013) dealt with the relationship between networks and education and found that differences in network elasticities are mostly as a result of education. More precisely, they highlighted that the more educated the existing diaspora is, the higher (lower) the proportion of skilled (less-skilled) migrants. This result

leads the authors to affirm that "the network effect might be higher for migrants with the same level of education" because they argued that "this might be related to the fact that the informational value of the network depends on the degree of matching between new and old migrants" (Beine & Salomone, 2013, p. 373). These claims cannot be directly tested by the authors because they have a cross-section of countries; therefore, they considered the skill ratio (ratio of skilled migrants over unskilled migrants) and found that "the more educated the existing diaspora is, the higher (lower) the proportion of skilled (less-skilled) migrants. This result suggests that the networks' effect might be higher for migrants with the same level of education" (Beine & Salomone, 2013, p. 373). Our results for Italy suggest that while this is true for graduate flows and for upper-secondary school flows, they do not hold up for the other educational levels.

Finally, the higher the magnitude of the estimated coefficients for the total migrants networks variable, the lower the education level of individuals who migrate is. On the contrary, the higher the magnitude of the education-specific stocks of migrants, the higher the educational level of migrants is. The former result is in line with Beine (2016) who found that in developed countries, where a higher proportion of skilled migrants are present, the effect of the networks is lower than in less developed countries. The idea is that since migration networks contribute to reducing migration costs for potential migrants and since these costs are most likely to be higher for the less-skilled rather than for the high-skilled, then those who are the least educated benefit the most from networks generated by total migrants. The latter result suggests that also for the most skilled migrants, there is a cost-reducing effect of migrants networks, but this effect is driven by the *education-specific* stock of migrants, rather than by the *total* stock of migrants.

9. CONCLUDING REMARKS

This paper has examined how migration flows by educational attainment respond to the standard macroeconomic and demographic variables. Our results prove that the reaction of migration flows is quite heterogeneous depending on migrant educational level. We have explored the role of two different migrants networks variables: *total* migrants networks and *education-specific* migrants networks, which is an important novelty of this paper. To the best of our knowledge, no one has investigated the different roles of migrants networks by educational level on migration flows when the latter are divided into five different educational levels. We have also contributed to the literature by exploring the role of regional human capital, separately as a push and pull factor, in conjunction with migration flows disaggregated by educational level.

With regards the role of explanatory variables at origin, per capita GDP is robustly linked with migration flows with a magnitude that is inversely related to the educational level of migrants. Indeed, for graduate migration flows, it acts as a push factor, whereas for all remaining flows, it operates as a stay-at-home factor. We interpret these results together with the negative role of human capital at origin for the same category of migrants, and in light of the fact that returns-to-skills for the highly skilled individuals in the southern regions are higher than those in the center-northern regions, as proof of the validity of the Borjas' (1987) model.

In general, variables at destination display a better explicative power when compared with variables at origin. Per capita GDP has a positive role as a pull factor for graduates, upper-secondary school and lower-secondary school education holders. Conversely, for primary school migrants and migrants without formal schooling, per capita GDP acts as a stay-away factor. As for human capital, also at destination, a clear inverse relationship between migrant educational level and the sensitiveness of migration flows is evident. These results mirror those obtained at origin and give strength to the validity of the Borjas' (1987)

model in explaining migration flows based on returns-to-skills differentiated between southern and center-northern regions.

Finally, very interesting results have been found regarding the differentiated role of migrants networks on migration by educational level. Migration flows by educational level react differently to the two migration networks variables. In particular, the impact of the total migration networks decreases as the migrants skill level increases; conversely, the impact of the education-specific migration networks increases as the migrants' skill level increases.

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[1] These differences have been extensively studied in the political (Vaccaro, 1995), sociological (Putnam, 1993), and historical (Salvemini, 1955) perspectives.

[2]Among the few studies on the role of networks in the context of internal migration, see Zhao (2003) for China, Peeters (2012) for Mexico, and Chakrabarti & Sengupta (2017) for the US.

[3]It is worth highlighting that theoretical models and estimation strategies different from those briefly illustrated here also exist. For example, Beine et al. (2016) showed that when the potential migrant optimizes his/her utility along with all his/her lifetime, the more appropriate estimator is the common correlated effects (CCE) advocated by Pesaran (2006). Such an estimator has been used in previous empirical research regarding migration flows in Italy, showing mixed results (Piras, 2017, 2020). On the contrary, in a study on international migration flows to Spain, Bertoli & Fernández-Huertas Moraga (2013) found that the CCE estimator outperforms the fixed effects estimator. More recently, Kapetanios, Serlenga & Shin (2020) proposed an innovative three-dimensional common correlated effects (3DCCE) estimator with a hierarchical multi-factor error components specification and used it to study interprovincial migration in Canada. In the present paper, all estimates have also been run with the CCE estimator. In general, the results show a much less explicative power with respect to the various fixed effects specifications outlined above.

[4]It should be noted that this test has the null hypothesis of *weak* cross-sectional dependence and it differs from another test based on Pesaran (2004) which has the null hypothesis of *strong* cross-sectional independence. Since the restrictions imposed by Pesaran (2004) are too strong and unlikely to be satisfied in large panels, it seems more reasonable to test for weak rather than strong cross-sectional correlation. Pesaran himself claims that "The null of weak cross-sectional dependence also seems more appropriate than the null of cross-sectional independence in the case of large panel data models where only pervasive cross-dependence is of concern" (Pesaran 2015, p. 1091).

[5] Further details on how we built these variables will be given in the next section.

[6]The data set used in the paper will be made available by the author upon request.

[7]In the figure, we take 2012 as a final year since in 2013, ISTAT aggregates primary school and no schooling into a single category. Also, in the empirical analysis, the time span for these two categories of migrants ends in 2012 rather than in 2013.

[8]The total stock of migrants considers total migration flows rather than education-specific flows.

[9]In general, results of the 3-FE model are similar to the 2-FE model, whereas results of the Ortega-Peri(b) model outperform both the Ortega-Peri(a) and the Anderson. As already stated, we decided to focus on the South to the Center-North flow because this has been the main direction of internal migrants. However, we have also run the regressions for the 2FE and the Ortega-Peri(b) model considering the full bilateral sample of Italian regions. The results, not reported here but available upon request, are less satisfying both in terms of residual test diagnostics and of the significance of estimated parameters. Yet, the great heterogeneity of estimated elasticities depending on the specific skill level of migration flows that we show in this section emerges also from the whole sample of Italian regions.

[10]A statistically significant role for human capital at origin for lower-secondary school migration flows is detected in the 3-FE and the Ortega-Peri(a) models shown in Table B3 in Appendix B.

[11]The average per capita GDP in 2013 in the South was 16,902 euros, and such a level does not seem to be so low that a would-be graduate migrant could not afford the cost of migration.

[12]Similar results, not discussed here but reported in Table B6 in Appendix B, are obtained with the 2-FE model.

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TABLE 1: Migration flows: first ten region-pairs corridors.

Region-pairs (year)	Graduates	Region-pairs (year)	Upper-secondary school	Region-pairs (year)	Lower-secondary school	Region-pairs (year)	Primary school	Region-pairs (year)	No schooling
Campania-Lazio (2012)	2206	Campania-Lazio (2012)	3628	Campania-Em.Rom (2010)	3478	Campania-Lazio (1989)	4719	Campania-Lazio (1990)	4132
Campania-Lombardia (2012)	2123	Campania-Lazio (2000)	3074	Campania-Em.Rom (1999)	3248	Campania-Lazio (1987)	4234	Campania-Lazio (1991)	4090
Campania-Lazio (2013)	2107	Campania-Lazio (2011)	2728	Campania-Em.Rom (2001)	3046	Sicilia-Lombardia (1989)	4120	Campania-Lazio (1992)	3707
Campania-Lombardia (2013)	2102	Campania-Lazio (2008)	2712	Sicilia-Lombardia (2000)	3028	Sicilia-Lombardia (1988)	3476	Sicilia-Lombardia (1990)	3122
Sicilia-Lombardia (2013)	2003	Campania-Lazio (2006)	2699	Sicilia-Lombardia (1999)	3003	Sicilia-Lombardia (1987)	3473	Sicilia-Lombardia (1991)	2644
Puglia-Lombardia (2013)	1850	Campania-Lazio (2005)	2695	Sicilia-Lombardia (1998)	2975	Puglia-Lombardia (1989)	3332	Campania-Lazio (1980)	2628
Campania-Lombardia (2011)	1806	Campania-Lazio (2002)	2663	Campania-Em.Rom (2002)	2771	Campania-Lazio (1988)	3196	Sicilia-Lombardia (1992)	2572
Sicilia-Lombardia (2012)	1789	Campania-Lazio (2010)	2613	Campania-Lazio (2012)	2760	Sicilia-Lombardia (1990)	3018	Sicilia-Lombardia (1980)	2466
Sicilia-Lombardia (2010)	1768	Campania-Lazio (2001)	2591	Sicilia-Lombardia (2001)	2739	Calabria-Lombardia (1989)	3012	Sicilia-Lombardia (1985)	2309
Campania-Lombardia (2010)	1764	Campania-Lazio (2013)	2590	Sicilia-Lombardia (1996)	2593	Sicilia-Lombardia (1981)	2992	Campania-Lazio (1983)	2288

TABLE 2: Graduates migration flows.

	2-FE	Ortega-Peri (b)
	(1)	(2)
PANEL A - VARIABLES AT ORIGIN		
Per capita GDP	1.15***	1.48***
	[0.33]	[0.35]
Unemp. rate	0.17***	0.15*
	[0.06]	[0.09]
Population	2.18***	2.15***
	[0.58]	[0.74]
Human capital	-1.27***	-1.55***
	[0.40]	[0.48]
PANEL B - VARIABLES AT DESTINATION		
Per capita GDP	1.50***	1.50***
	[0.21]	[0.39]
Unemp. rate	0.14*	0.13
	[0.08]	[0.08]
Population	2.78***	2.94***
	[0.34]	[0.47]
Human capital	-5.45***	-5.42***
	[0.62]	[0.67]
Graduate migrants networks	0.56***	0.46***
	[0.06]	[0.09]
Origin	----	256
Adj_R^2	0.95	0.95
CD test (*p*-val.)	0.007	0.006

Notes: units 96; total observations: 3168. Robust standard errors (clustered at origin-destination) in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. In column (2) the reported coefficients for monadic variables at origin are those of the second-stage regressions of the two-step procedure employed to estimate the Ortega-Peri(b) model. Origin is the number of observations used in the second stage. CD test is Pesaran (2015) test for weak cross-sectional dependence. The user-written STATA routine xtcd2 has been used (Ditzen, 2016). See the main text for more details.

TABLE 3: Upper-secondary school migration flows.

	2-FE	Ortega-Peri
	(1)	(2)
PANEL A - VARIABLES AT ORIGIN		
Per capita GDP	-0.53**	-0.22
	[0.24]	[0.24]
Unemp. rate	0.03	0.05
	[0.05]	[0.07]
Population	0.41	0.61
	[0.44]	[0.48]
Human capital	-0.71**	-1.20***
	[0.34]	[0.37]
PANEL B - VARIABLES AT DESTINATION		
Per capita GDP	0.55***	0.53*
	[0.17]	[0.28]
Unemp. rate	-0.19***	-0.20***
	[0.06]	[0.06]
Population	2.52***	2.90***
	[0.29]	[0.42]
Human capital	-2.11***	-1.93***
	[0.47]	[0.63]
Upper sec. school migrants networks	0.58***	0.45***
	[0.06]	[0.12]
Origin	----	258
Adj_R^2	0.97	0.97
CD test (*p*-val.)	0.746	0.667

Notes: See TABLE 2 and the main text for more details.

TABLE 4: Lower-secondary school migration flows.

	2-FE	Ortega-Peri (b)
	(1)	(2)
PANEL A - VARIABLES AT ORIGIN		
Per capita GDP	-1.09***	-1.15***
	[0.22]	[0.30]
Unemp. rate	0.30***	0.28***
	[0.05]	[0.07]
Population	-0.46	-0.85
	[0.46]	[0.57]
Human capital	0.55	-0.11
	[0.35]	[0.43]
PANEL B - VARIABLES AT DESTINATION		
Per capita GDP	1.08***	1.09***
	[0.17]	[0.20]
Unemp. rate	-0.24***	-0.25***
	[0.05]	[0.07]
Population	2.51***	2.77***
	[0.25]	[0.37]
Human capital	-1.90***	-1.71**
	[0.43]	[0.72]
Lower sec. school migrants networks	0.75***	0.66***
	[0.06]	[0.10]
Origin	----	257
Adj_R^2	0.97	0.97
CD test (*p*-val.)	0.129	0.119

Notes: See TABLE 2 and the main text for more details.

TABLE 5: Primary school migration flows.

	2-FE	Ortega-Peri
	(1)	(2)
PANEL A - VARIABLES AT ORIGIN		
Per capita GDP	-1.58***	-1.21***
	[0.43]	[0.39]
Unemp. rate	0.12*	0.15**
	[0.07]	[0.06]
Population	-1.91*	-0.45
	[1.08]	[0.79]
Human capital	3.98***	1.41***
	[0.73]	[0.46]
PANEL B - VARIABLES AT DESTINATION		
Per capita GDP	-0.72***	-0.75
	[0.23]	[0.46]
Unemp. rate	-0.46***	-0.46***
	[0.09]	[0.12]
Population	1.57***	1.41**
	[0.50]	[0.59]
Human capital	3.01***	3.00***
	[0.72]	[0.81]
Primary school migrants networks	0.57***	0.64***
	[0.09]	[0.16]
Origin	----	258
Adj_R^2	0.94	0.95
CD test (*p*-val.)	0.504	0.552

Notes: See TABLE 2 and the main text for more details.

TABLE 6: No schooling migration flows.

	2-FE	Ortega-Peri (b)
	(1)	(2)
PANEL A - VARIABLES AT ORIGIN		
Per capita GDP	-0.06	0.69
	[0.52]	[0.73]
Unemp. rate	0.18*	0.23*
	[0.10]	[0.12]
Population	-2.83**	-0.35
	[1.17]	[1.69]
Human capital	7.52***	5.49***
	[0.74]	[0.83]
PANEL B - VARIABLES AT DESTINATION		
Per capita GDP	-2.22***	-1.89***
	[0.36]	[0.71]
Unemp. rate	-0.58***	-0.58***
	[0.11]	[0.11]
Population	0.84*	1.32
	[0.49]	[1.22]
Human capital	7.01***	6.72***
	[0.90]	[1.91]
No schooling migrants networks	0.73***	0.53**
	[0.02]	[0.21]
Origin	----	257
Adj_R^2	0.90	0.92
CD test (*p*-val.)	0.138	0.018

Notes: See TABLE 2 and the main text for more details.

TABLE 7: Migration flows with total and education-specific stock of migrants (Ortega-Peri(b) model).

	(1)	(2)	(3)	(4)	(5)
	Graduates	Upper-secondary school	Lower-secondary school	Primary school	No schooling
PANEL A - VARIABLES AT ORIGIN					
Per capita GDP	-0.31	-0.25	-1.11***	-1.96**	-0.03
	[0.23]	[0.24]	[0.33]	[0.81]	[0.85]
Unemp. rate	0.14***	-0.00	0.26***	0.22**	0.16
	[0.05]	[0.07]	[0.07]	[0.18]	[0.14]
Population	0.67	0.64	-0.57	-1.32	-3.02
	[0.44]	[0.46]	[0.65]	[2.46]	[2.06]
Human capital	0.45	-0.75**	0.16	3.85***	7.09***
	[0.33]	[0.35]	[0.46]	[0.96]	[1.03]
PANEL B - VARIABLES AT DESTINATION					
Per capita GDP	1.48***	0.44	0.97***	-0.70*	-2.15***
	[0.40]	[0.28]	[0.20]	[0.36]	[0.74]
Unemp. rate	0.13*	-0.20***	-0.24***	-0.27***	-0.50***
	[0.08]	[0.06]	[0.07]	[0.10]	[0.10]
Population	2.78***	2.55***	2.02***	-1.36***	-1.09
	[0.65]	[0.38]	[0.35]	[0.45]	[1.23]
Human capital	-5.48***	-1.99***	-1.52**	1.15*	4.88***
	[0.71]	[0.61]	[0.74]	[0.18]	[1.76]
Total migrants networks	0.06	0.25**	0.59***	2.03***	1.43***
	[0.12]	[0.12]	[0.15]	[0.18]	[0.29]
Education-specific migrants networks	0.45***	0.31**	0.24	-0.90***	-0.30
	[0.09]	[0.15]	[0.16]	[0.22]	[0.35]
Adj_R^2	0.95	0.97	0.97	0.96	0.93
CD test (*p*-val.)	0.006	0.600	0.092	0.983	0.040

Notes: units 96; total observations: 3168. Robust standard errors (clustered at origin-destination) in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The reported coefficients for monadic variables at origin are those of the second-stage regressions with 257 observations. See the main text for more details.
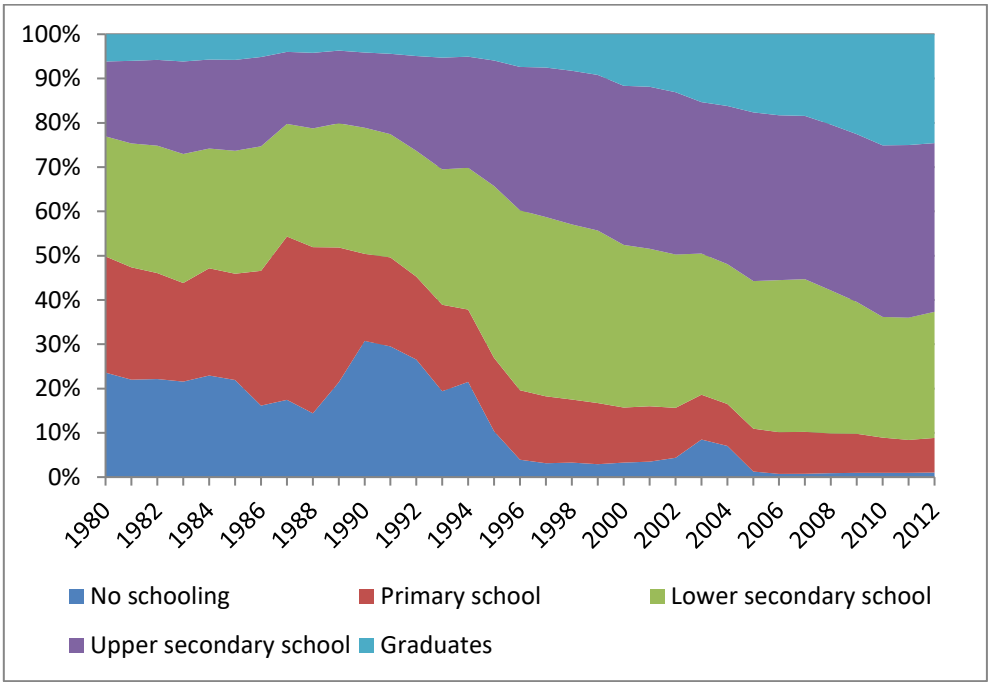
FIGURE 1: Evolution of migration flows by educational attainment.