Income Redistribution and Self-Selection of Immigrants

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Abstract: We analyze the effects of governmental redistribution of income on migration patterns, using an Italian administrative dataset that includes information on almost every Italian citizen living abroad. Since Italy takes a middle ground in terms of redistribution, both the welfare-magnet effect from more redistributive countries and the propensity of the high-skilled to settle in countries with lower taxes can be empirically studied. Our findings confirm the hypothesis that destination countries with more redistribution receive a negative selection of Italian migrants. This holds true after accounting for many individual and country level covariates, migration costs, and when testing for stochastic dominance of the skill distributions of migrants and stayers. Policy simulations are run in order to gauge the magnitude of these migration effects. Based on estimated elasticities, we find that sizable increases in the amount of redistribution in Italy have small effects on the skill composition of the resident population.

Keywords: Roy-Model, Self-selection, Migration, Redistribution.

JEL: D31, F22, H23, J61, O15.

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1 Introduction

The resilience of welfare states in times of "globalization" heavily depends on the impact of reduced barriers to international labor mobility upon the ability of domestic governments to contain income inequality within their borders. Namely, governmental income redistribution may be impaired by the opposite migration incentives it generates along the skill distribution: at the bottom, by acting as a welfare magnet towards low-skilled foreigners; at the top, by inducing the emigration of high-skilled workers. In combination, those effects may severely limit the degree of progressivity that national tax-transfer systems can afford. Despite the prominent role played by arguments of this nature in policy debates, their empirical relevance is still subject to much debate. Clearly, a quantification of the effects of redistributive policies on migration flows is a necessary pre-condition for a reliable evaluation of such policies. In this paper, we contribute to the assessment of those effects by studying a unique administrative dataset that covers almost the entirety of the Italian migrant population worldwide and allows us to recover migration flows from Italy since 1960.

Italy is one of the countries in the world with the highest absolute number of emigrants. The dataset we scrutinize encompasses 88% of all Italians registered abroad, more than four million people. They account for the Italian population in 13 foreign countries: Argentina, Australia, Belgium, Brazil, Canada, France, Great-Britain, Germany, The Netherlands, New-Zealand, Switzerland, the US, and Venezuela. Of these, about 1.3 million personally have migration experience (i.e. were born in Italy). To the best of our knowledge, the only other study testing the selection process of migrants with administrative data on almost the entire population of emigrants is Borjas et al. (2018) using Danish migration register data.[1]

Italy is an ideal laboratory to explore the effects of domestic income redistribution on migration patterns. Previous micro-data based studies mostly deal with migration flows from developing countries to developed countries, hence from typically poor and unequal to rich and less unequal

[1]The fifteen countries with the highest number of emigrants are Russia, Mexico, India, Bangladesh, Ukraine, China, UK, Germany, Kazakhstan, Pakistan, Philippines, Italy, Turkey, Afghanistan, and Morocco. Denmark places 122th on this ranking with about 240,000 emigrants (Global Migrant Origin Database v4, Migration DRC).

countries (as pointed out by Hatton, 2014), or as mentioned above from Denmark, a country with a compressed income distribution, to the rest of the world. In contrast, the current study proper investigates migration outflows from a country with medium levels of inequality and redistribution, Italy, from which millions migrated either to countries with less progressive tax systems, like Argentina, Brazil, Venezuela, New Zealand and the US, or to countries with more progressive ones, like Belgium, France, Germany and the Netherlands. Hence, we are able to empirically evaluate both effects of income redistribution on migration: the welfare-magnet effect at the bottom, and the rich-repulsion effect at the top of the income distribution.

We find that variations in time and space of governmental redistribution of income contribute to explaining migration patterns out of Italy over the last half-century. A larger amount of income redistribution in a destination country is associated with negative selection of Italian migrants with respect to their skills. This relationship holds even after controlling for individual characteristics of the migrants, country characteristics like GDP per capita and the unemployment rate, migration costs (approximated by the distance of the country of residence to the Italian border), the existence of migration agreements between the two countries, and the share of migrants from the same Italian province residing in the same country (an indicator of network effects), as well as country fixed effects. Furthermore, the skill distribution of Italian migrants in countries with relatively low levels of redistribution stochastically dominates the distribution of Italian migrants in countries with high levels of redistribution as well as the distribution of Italian residents. We also find evidence for selection on unobservable characteristics, measured by the probability of being unemployed or having a distinctively high occupational position, given one's level of education.

Results from a discrete-choice model of the decision to migrate, one that includes demographic characteristics and place characteristics of the country of destination, offer further support for the hypothesis that more redistribution adversely affects the skill composition of the domestic workforce. Based on such an empirical model, we perform a simple policy experiment in order to gauge the magnitude of the involved effects. Holding the tax-transfer-system in all destination countries fixed at their current level, we investigate the impact of an additional affine budget-neutral redistributive policy in Italy on the migration behavior of Italian citizens and the resulting skill composition of the resident population in Italy. Our initial policy experiment has the Italian government introducing a yearly demogrant of one thousand USD per adult, implying a rise of public expenditures in Italy of about two percentage points of GDP. Such a policy is found to lower the outflows of low-skilled individuals and increase the outflows of high-skilled individuals, and to have a negligible impact on the migration of medium-skilled workers. Despite its first-order fiscal magnitude, the quantitative impact of this policy on the composition of the resident workforce in Italy turns out to be of the second order. When we raise the demogrant, and thus the degree of progressivity of the policy experiment, the same qualitative pattern prevails but the effects become quantitatively more important. However, even a five-fold increase of the demogrant does not lead to a substantial shift of the Italian skill distribution to the left. We therefore conclude that in Italy the effects of more redistribution on the skill composition of migration flows are statistically significant, but have limited significance for the evaluation of redistributive policies.

The current paper is mainly related to two strands of literature, one on migration and the predictions of the Roy model, and one on income redistribution under the threats of migration. A large body of work on migration has pointed out that migrants are not a random draw from the population of their home country, neither are they undistinguishable in their observable and unobservable characteristics from the native population of their host country. Besides this basic consensus, different findings on the patterns characterizing the self-selection of immigrants coexist.

In an influential paper, Borjas (1987) applies the Roy model of self-selection and argues that the returns to human capital in source and destination country determine whether high or low skilled individuals migrate: the higher are the returns to human capital in a country, the more high skilled individuals will tend to migrate to this country. This hypothesis has been empirically confirmed by Moraga (2010) and Parey et al. (2017), among others. On the other side, Chiswick (1999) argues in favour of a general positive selection of migrants, in line with the predictions of standard human capital theory since Sjaastad (1962); this hypothesis has been confirmed in empirical studies by Liebig and Sousa-Poza (2004) and Chiquiar and Hanson (2005).

The empirical measurement of returns to skills has not been uniform in this branch of literature. Some studies focus on the educational attainment, some on earnings, and some on measures of income redistribution. We employ all of these variables in order to approximate the relative level of returns to skills, and show that consistent results are obtained throughout.

Another crucial issue in this literature is the availability of suitable data sources to test the theory. Most existing studies on the self-selection of migrants rely on macro-data containing aggregate information on the characteristics of migrants, census data which allows the analysis of flows and stocks of migrants from one particular country to another (mostly from Mexico to the US), or survey data reporting pre-migration earnings or migration intentions. Further evaluations using novel data sources therefore seem necessary to deepen our understanding about the process of migrants' self-selection. As we explain in detail in Section 3, the administrative dataset we use offers the possibility to substantially enrich the empirical basis for a more comprehensive assessment of the Roy model.

We complement our administrative dataset with Italian household survey data that can be used to measure selection on observable characteristics predicting the counterfactual labour earnings of immigrants had they stayed in Italy. We also estimate the relative educational position of every migrant with respect to his or her reference group, i.e. non-migrants born in the same year living in the Italian region where the individual resided before moving to the foreign country. Furthermore, we use harmonized household survey data from the Luxembourg Income Study to estimate the net monetary returns to migration in the destination country, as well as the counterfactual potential returns in all other possible destination countries as well as in Italy.

The second line of research to which we contribute is the public economics of redistribution in the presence of international migration. An early goal of this line of research was to examine the welfare-magnet hypothesis, i.e. the claim that generous social welfare programs prompt immigration of individuals who are more likely to use such programs. A number of empirical studies - especially in the wake of the EU enlargements that introduced freedom of movement for Eastern European workers - found rather little support for that hypothesis (Levine and Zimmerman, 1999; Gelbach, 2004; McKinnish, 2007; Giorgi and Pellizzari, 2009; Giulietti et al., 2013; Skupnik, 2014). Immigration seems to be primarily driven by differentials in unemployment and wages between the source and the destination countries, rather than by the relative magnitude of social transfers. Razin and Wahba (2015) suggest that such evidence may be confounded by heterogeneous legal frameworks that restrict international mobility, and find strong support for the welfare-magnet hypothesis in free-migration regimes. We control for labor mobility restrictions and also find that countries with more generous welfare programs tend to attract a larger fraction of low-skilled Italian workers. However, our policy experiment corroborates the notion that such effects are relatively modest.

The role played by tax-driven migrations in shaping optimal tax-transfer systems has been investigated in a number of theoretical articles (e.g. Simula and Trannoy, 2010; Bierbrauer et al., 2013; Lehmann et al., 2014; Ruiz del Portal, 2017). Numerical simulations based on extended Mirrlees-type models have shown that such effects are potentially large, particularly with respect to the welfare of the households at the top of the skill distribution. Empirical investigations that exploit the coexistence of free movement and local tax autonomy within Switzerland, however, found relatively small effects. By way of an example, according to Liebig et al. (2007) they are not large enough to offset the revenue-increasing effect from a rise in tax rates. Empirical results with the same flavor have been obtained for mobility across US states (e.g. Young and Varner, 2011) and Canadian provinces (e.g. Day and Winer, 2006). Some recent papers have challenged this view by pointing to substantial tax-induced labor mobility in various settings. Kleven et al. (2013a) examine the European football labor market, Kleven et al. (2013b) study the inflow in Denmark of foreign top earners under a preferential tax scheme, Akcigit et al. (2016) look at the international mobility of inventors, Moretti and Wilson (2017) consider the internal migration of star scientists in the US. All of these papers estimate large elasticities of migration with respect to taxation. However, if the considered groups are small, this might be consistent with overall small fiscal effects from migration.

The remainder of the paper is organized as follows. Section 2 briefly sketches the theoretical framework that motivates the empirical research on the self-selection of migrants, and discusses its evaluation by the literature. Section 3 describes the distinct data sources and measurement procedures we employ in the subsequent analysis. Section 4 offers a first impression of the relationship between redistribution and migration found in the data, by means of simple bivariate correlations. Section 5 presents a battery of empirical exercises aimed at assessing the statistical significance of the relationship between redistribution and migrants' self-selection. Section 6 describes our redistributive-policy experiment and shows its impact on the skill composition of the resident population. Section 7 concludes.

2 Returns to Skills and Self-selection of Migrants

The working hypothesis that underlies much of the literature, including the current paper, is that migration decisions are driven by the quest for a potentially higher level of disposable income, net of migration costs. Because disposable incomes are affected by governmental income redistribution in each country, host countries characterized by a less progressive tax-transfer system are expected to attract relatively more high-skilled migrants, while those with a more progressive system will tend to attract migrants with a lower skill level.

In a nutshell, the logic of the theory that underpins these statements can be displayed in a basic model with three countries: a country of origin (I), an egalitarian destination country (G), and an inegalitarian destination country (U). For the sake of the argument, suppose that all three countries have access to the same constant returns-to-scale technology and individuals in I can obtain the same productivity in any country, equal to their skill level $s \geq 0$; individuals differ with respect to their skill level. Assume that in every country an affine tax schedule redistributes income, so that disposable income (gross of migration costs) in country $c \in \{I, G, U\}$ reads:

$$y_c = \omega_c + (1 - t_c)s, \tag{1}$$

where ω_c is the social minimum (a demogrant) and $1 - t_c \equiv \rho_c$ determines the marginal net return to skill in country c. Our assumptions on progressivity are that $\rho_U > \rho_I > \rho_G$ and $\omega_U < \omega_I < \omega_G$.

If migrations costs are negligible for individuals who may migrate from I, their location choice will maximize disposable income y_c. In any equilibrium in which every country (including I) attracts individuals at some skill level, the resulting pattern will be of the type illustrated in Figure 1. Individuals from I with a skill level lower than s_1 will migrate to G, because what they give up in terms of higher taxes is more than compensated by the demogrant they receive. Individuals with a skill level higher than s_2 will migrate to U, because what they give up in terms of a lower demogrant is more than compensated by the lower taxes they must pay. Individuals with a skill level between s_1 and s_2 will optimally refrain from migrating and remain in I.

If migration costs m_c - expressed in monetary terms - are non-negligible, migration decisions will maximize $y_c - m_c$ by choice of $c \in \{I, G, U\}$. If migration costs are not too large in absolute terms and uniform across all individuals, the resulting migration pattern will exhibit the same type of selection as in Figure 1. Setting $m_I = 0$, the skill thresholds will be given by

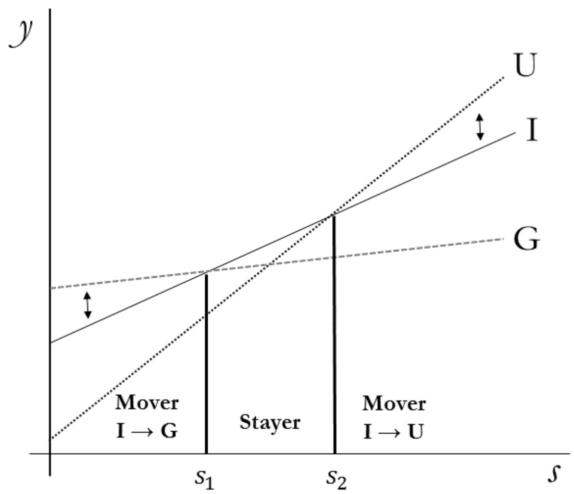
$$s_1 = \frac{\omega_G - m_G - \omega_I}{\rho_I - \rho_G}, \tag{2}$$

$$s_2 = \frac{\omega_I + m_U - \omega_U}{\rho_U - \rho_I}. \tag{3}$$

If migration costs vary across individuals, but are uncorrelated with the skill level, the same migration pattern will arise in statistical terms: e.g., country G may attract migrants with a high level of skills who exhibit a low level (possibly negative) of m_G, but the average skill level of the received migrants will be lower than both the average skills of migrants to U (the less egalitarian destination) and the average skills of those who stay in I.

The predictions of theoretical frameworks of this kind were first scrutinized using data on international and internal migrants in the US: Borjas (1987) finds that the degree of income inequality in the home country, a proxy measure for the returns to skills, is a predictor for the type of selectivity of migrants, while Borjas et al. (1992) show that interstate variations in the returns to skills affect

Figure 1: Positive and Negative Self-Selection of Migrants



the skill structure of migration inflows. In contrast, Chiswick (1999) states that immigrants also tend to be favourably self-selected in the presence of higher levels of income inequality and Borjas (1987)'s empirical results only show that income inequality attenuates the degree of selection, but not the generally positive selection pattern. Liebig and Sousa-Poza (2004) support this claim in an analysis of cross-country survey data on migration intentions. Recent studies that review the empirical literature and also test this theory are Parey et al. (2017) and Patt et al. (2017).

A likely explanation for the diverging results of some empirical studies points to the important role of migration costs for the migration decision and the selection process. For instance, Chiquiar and Hanson (2005) show that if migration costs are negatively correlated with the skill level, both positive and negative self-selection into countries with higher returns are possible equilibrium outcomes. In turn, migration costs are determined not only by transportation costs and the value of friends, family, and culture left behind, but also by immigration policies and migration networks (Hatton, 2014). McKenzie and Rapoport (2010) find that self-selection is more likely to be positive in places with sparse migration networks and more likely to be negative in places where many migrants from the same origin countries reside.

3 Data & Measurement

3.1 Administrative data on Italians abroad

The micro-data basis of our investigation is the Registry of Italians resident abroad (*Anagrafe degli italiani residenti all'estero*, AIRE), an administrative registry dataset that is managed by the Italian Ministry of Foreign Affairs. All Italians who have resided abroad for at least one year or were born outside of Italy are required to register to the AIRE by law.[2] Furthermore, some bureaucratic tasks, e.g. renewing an Italian passport or ID card, and voting in Italian elections, are only possible for Italian migrants if they are recorded in the AIRE; crucially, Italians who live abroad are generally liable to the Italian fiscal authority for paying personal income tax, unless they are registered in the AIRE.

Our dataset encompasses approximately 88% of all Italian citizens registered in the AIRE worldwide; it provides individual information on 4,079,646 registered Italian citizens in 13 different foreign countries between 2014 and 2015, as well as information on their spouses and children without Italian citizenship.[3] Table 1 shows the number of individuals in our dataset, subdivided according to country of residence, birth year, and year of arrival in the host country.

The individual information contained in the registry data at our disposal includes: date of birth, date of arrival in the host country, sex, place of birth, place of residence, education, occupation and the last municipality of residence in Italy before migration.

[2]Enrollment is a citizen's right and duty established by law no. 470/1988. Only Italian civil servants working abroad, for instance at embassies or consulates, diplomatics, and Italian military in service at NATO facilities located abroad are not required to register to the AIRE.

[3] The number of Italians registered in AIRE on January 1, 2015, is 4,636,647 (Fondazione Migrantes, 2015). The only country missing in our sample of the ten countries with the highest concentration of Italian immigrants worldwide in 2015 is Spain. Furthermore, our data for France only includes Italian citizens registered in two out of five consulates (about 50 % of all Italians residing in France). All estimations excluding France are not significantly different to our main results and can be found in the Supplemental Material. A comparison of the number of Italian migrants in AIRE and the International Migration Database of the OECD is also included in the Supplemental Material.

Table 1: Number of registered individuals in the registry of Italians resident abroad (AIRE)

	Registered in AIRE				
	Total	Italian citizenship	Born in Italy	Born 1940-1985	Arrival 1960-2015
ARG	1,191,059	893,974	119,008	50,044	7,271
AUS	221,292	149,246	53,900	35,277	18,444
BEL	333,235	273,415	95,438	67,160	34,249
BRA	597,232	450,939	36,804	19,334	7,454
CAN	188,289	137,289	72,909	43,645	24,318
CH	695,081	607,084	220,133	168,060	117,636
FRA	214,512	170,023	70,736	45,468	23,785
GBR	308,077	263,916	130,100	87,127	60,511
GER	813,254	694,694	300,863	258,315	165,929
NLD	48,895	41,346	16,767	12,782	4,696
NZL	5,056	4,052	1,497	1,100	757
USA	334,093	250,176	133,498	97,212	67,086
VEN	218,351	143,492	28,801	14,097	4,972
Total	5,168,426	4,079,646	1,280,454	899,621	537,108

Notes: Subsequent columns show the respective subtotal. Our data for France only includes Italian citizens registered in two out of five consulates (about 50 % of all Italians residing in France).

We restrict our attention to Italians with own migration experience; thus, we focus on migrants that were born in Italy and exclude the foreign-born children and grandchildren of migrants (so-called second and third generation migrants) from our final sample. In order to ensure that one's skill is known at the time the individual decides to migrate, we concentrate on individuals who had already finished their educational career when migrating; thus we exclude all individuals that registered with AIRE when younger than 20 years of age. In order to avoid biases deriving from, first, individuals who have not yet finished their educational career, and secondly, differential mortality of people with different levels of education, we restrict our final sample to the age range 30 to 75, i.e. to the cohorts born between 1940 and 1985. Hence, our analysis pertains to migration from Italy that occurred between 1960 and 2015. Table 2 shows descriptive statistics for individual and country characteristics from our final sample.

How do the levels of education of Italian emigrants compare to those of the population in Italy? The answer to this question depends on the cohorts under consideration. Figure 2 allows one to compare the average years of education of Italians who migrated (Mover) to the average

Table 2: Descriptive Statistics of the Sample – Country Averages

	Year of birth	Year of arrival	Share of female	Years of education	Rural origin	Capital	Internal migrant	GDP p.c.	GDP growth	Unemployment rate	Distance (in tsd km)	Bilateral agreement	Policy toward high skilled
ARG	1948.48	1994.83	0.53	8.39	0.45	0.21	0.11	6.33	4.16	8.41	10.200	1	0
AUS	1958.68	1988.86	0.40	9.79	0.31	0.00	0.13	24.19	3.70	5.18	12.100	1	0
BEL	1960.24	1992.26	0.42	10.51	0.20	0.06	0.15	24.13	2.47	7.57	0.530	1	0
BRA	1961.08	2001.67	0.20	12.68	0.15	0.01	0.21	7.07	3.23	8.21	7.000	1	1
CAN	1952.83	1980.98	0.43	8.74	0.39	0.02	0.09	14.75	3.88	6.36	5.000	1	1
CH	1961.66	1994.45	0.39	10.28	0.32	0.01	0.16	49.66	1.71	3.06	0.000	1	1
FRA	1966.65	2000.83	0.46	13.23	0.17	0.32	0.18	30.62	1.80	9.18	0.000	1	0
GBR	1971.28	2004.40	0.42	13.17	0.17	0.48	0.17	35.29	2.18	6.68	0.900	1	0
GER	1960.66	1990.60	0.37	8.62	0.31	0.04	0.11	23.13	2.09	5.85	0.070	1	0
NLD	1973.91	2007.96	0.37	14.43	0.14	0.28	0.19	46.05	1.10	5.46	0.640	1	0
NZL	1970.54	2006.04	0.42	13.72	0.13	0.14	0.18	30.39	2.37	5.28	18.000	0	0
USA	1960.30	1993.88	0.43	11.58	0.20	0.01	0.14	30.13	2.87	6.12	6.100	0	1
VEN	1950.67	1983.97	0.40	10.36	0.24	0.47	0.16	3.88	3.32	8.45	7.700	0	.
Total	1962.10	1994.36	0.40	10.55	0.27	0.11	0.14	30.94	2.34	5.81	1.952	1	0

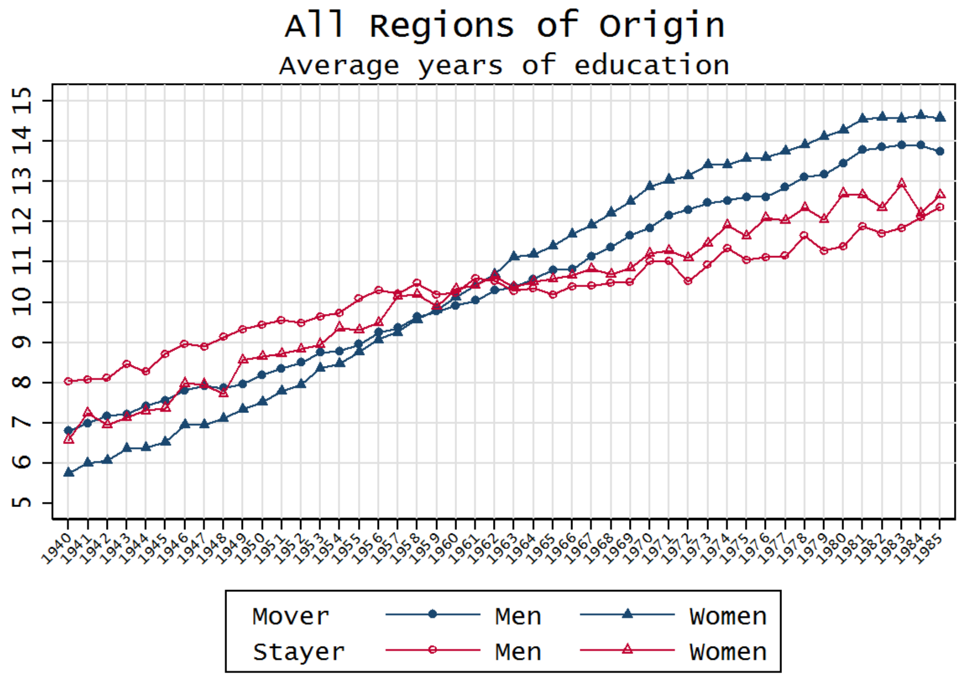
Sources: Individual characteristics from AIRE. Sample is restricted to people born in Italy, 30-64 years old, and who registered in AIRE after the age of 20. Unemployment rate, GDP growth, GDP per capita from World Bank Data. Distance to Italy measured from border to border (Google Maps). Migration agreement is equal to one if there is/have been bilateral migration agreements between Italy and the country of destination; information retrieved from different sources. Policies oriented towards high skilled is equal to one if the policies of the country in the last 50 years have been more oriented at attracting high skilled immigrants or disincentive low skilled immigrants; information retrieved from the DEMIG Policy Database.

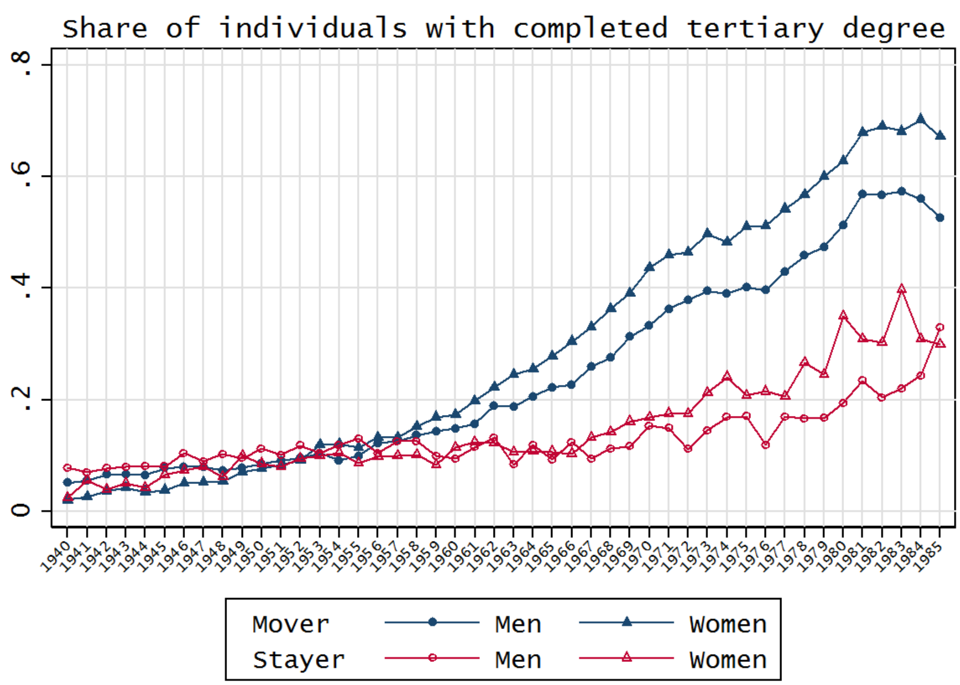
years of education of Italians living in Italy (Stayer) born in the same year.[4] On average, male and female Italians born between 1940 and 1961 and living abroad in 2015 have lower educational attainment than the average of the Italian population of people born in the same years. After this birth-year, subsequent cohorts of emigrants have a relatively higher average level of education than the stayers by about one year of education. It turns out that particularly the share of emigrants with a completed tertiary education degree experienced a dramatic increase. With respect to gender differences, movers and stayers share a common feature: older men have more education than women, while younger women are more educated than men.

In Italy, socio-economic variables differ considerably across macro-regions. Figure 3 shows the differences in average educational attainment between movers and stayers by Italian macro-region of origin, and across cohorts. Movers from the Center and the North of Italy have a constantly higher level of education than the stayers from the same regions, while movers from the South of Italy and the Islands have lower or similar average educational attainment as compared to stayers. These findings suggest that the region of origin contains valuable information when it comes to assessing the selection of migrants.

[4] Years of schooling are coded following this scheme: No school degree, 0 years. Uncompleted compulsory schooling, 5 years. Compulsory schooling, 8 years. Beyond compulsory education, 13 years. Tertiary degree, 16 years.

Figure 2: Average Years of Education of Italian Mover and Stayer by Year of Birth. Italians of all regional origins and subdivided by gender.





Source: Averages for Mover are own calculations using AIRE, averages for Stayer are own calculations using SHIW.

Figure 3: Average Years of Education of Italian Mover and Stayer by Year of Birth and Geo-graphic Macro-Region of Origin.

Source: Averages for Mover are own calculations using AIRE, averages for Stayer are own calculations using SHIW.

3.2 Earnings and income data

In order to evaluate the theoretical predictions described above, incomes and counterfactual incomes, both in Italy and the destination countries, must be estimated. This is why we complement the AIRE dataset with more detailed information that enables us to impute incomes to the individuals in our sample.

We use the Survey on Household Income and Wealth (SHIW) provided by the Bank of Italy as the main source of information on the origin country. The SHIW collects information on Italian households, including individual characteristics for each adult household member. For the present study, we use the comparable survey waves from 1977 to 2014, normalizing the sampling weights for each single year if more than one single wave is used for the analysis.

We employ this dataset to run an augmented Mincer regression of *log* labour earnings on the SHIW sample in 2014, and use the coefficients of that regression to predict the counterfactual *log* labour earnings that emigrants would have obtained, had they stayed in Italy.[5] The variables included in the regression are: years of schooling, age, quadratic age, sex, Italian region of origin, Italian region of birth, and an indicator on whether the individual is an internal migrant (i.e. does not live in the same region or did not migrate from the same region where he or she was born). To better capture lifetime earnings, for this exercise we exclude from the estimation individuals below 35 and older than 55 (see Bönke et al., 2015). Table 3 shows the OLS estimates in column (1).

To account for the selection of migrants in the earnings equation that could bias OLS estimates, we apply the Heckman selection procedure in two stages. In the first stage, the population weighted probability to emigrate is estimated on the pooled sample of stayer and mover, i.e. pooling SHIW and AIRE data.[6] Hereby, the number of emigrants born in the same year and in the same Italian region as the individual are included as further predictors of his or her probability of staying in Italy.[7]

[5]We estimate the Mincer regression on all individuals in SHIW data with positive labor earnings and then predict the log labor earnings also for all Italians in SHIW, including those with missing information about their labor earnings.

[6]For SHIW we use the data design weights. For AIRE we compute weights that counterbalance the observations with missing information on educational attainment.

[7]To approximate the total amount of emigrants for each birth cohort and Italian region of birth we use the AIRE data for the countries at our disposal.

Table 3: Augmented Mincer regressions to predict log labour earnings

Sample	Italians in Italy (SHIW)		Italians worldwide (AIRE+SHIW)
	(1)	(2)	(3)
	OLS	Heckman	Selection equation
Dependent variable	log Labour Earnings	log Labour Earnings	Stayer (0/1)
Female	-0.401***	-0.374***	0.116***
	(0.0257)	(0.0309)	(0.0246)
Age	0.0220	0.0180	0.00484
	(0.0338)	(0.0341)	(0.0362)
Age × Age	-0.0000830	-0.0000264	0.00000324
	(0.000370)	(0.000374)	(0.000398)
Years of education	0.0633***	0.0547***	-0.0358***
	(0.00406)	(0.00694)	(0.00365)
Internal migrant	0.0273	-0.0216	-0.157***
	(0.0592)	(0.0652)	(0.0452)
Inverse Mills Ratio		2.521	
		(1.596)	
Number of emigrants born in the same year and region			-0.000204***
			(0.0000748)
_cons	8.330***	8.408***	2.462***
	(0.761)	(0.767)	(0.814)
Region of origin and birth controls	Yes	Yes	Yes
Observations	2754	2754	157836
R^2	0.273	0.274	

Notes: Weighted regressions using survey design waves from SHIW and constructed population weights for AIRE. Robust standard errors. Statistical significance level * 0.1 ** 0.05 *** 0.01. Source: SHIW and AIRE, own estimations.

The assumption is that this captures the predictive power of network effects and diasporas on individual migration decisions, without exerting a direct effect on earnings in 2014. Then, the inverse Mills Ratio for each observation, estimated in the first stage, is included in the earnings regression as an additional control variable to obtain unbiased estimates. Table 3 shows the coefficients from this procedure in column (2) and the first-stage estimates in column (3).

The estimates in Table 3 show that the coefficients change only slightly and the coefficient of the Mills ratio is not significantly different from zero. This means that the observable characteristics included in the regression account for selection properly and we can safely adopt the predictions from the OLS estimates. We report results from using the counterfactual labour earnings estimated with the Heckman procedure in the Supplementary Material. These results do not significantly differ from those presented in the main text.

The key variable in the migration model sketched above is the net income the individuals receive as a consequence of locating in a given country. We use harmonized microdata from the Luxembourg Income Study (LIS) to estimate the net incomes in the country of residence of emigrants, their counterfactual net incomes in Italy, and in each of the other possible destination countries. Furthermore, we use that dataset to compute the net incomes of stayers in Italy, as well as their counterfactual incomes in all possible destinations. This part of the analysis is based on survey samples of every single destination country around the year 2014. Unfortunately, LIS data is not available for Argentina, New Zealand, and Venezuela. Furthermore, the last available survey for Belgium dates back to the year 2000. Therefore, whenever net incomes are involved, our results are derived from the remaining nine possible destination countries and Italy.

Using country-specific LIS data – on a sample of the resident population excluding people with disabilities – we estimate an augmented Mincer regression of disposable household income on a set of individual controls that include sex, age, quadratic age, education, and indicators as to whether the individual is married and whether at least one child lives in the household. The results table showing the coefficients of these regressions for each country can be found in the Supplemental Material. Then, we predict the disposable incomes (in international US Dollars, and applying Purchasing Power Parity) of Italian migrants in all possible destinations and in Italy using the coefficients of this regression. Returns to migration are then defined as the difference between predicted net incomes in the destination country and the counterfactual net income in Italy.

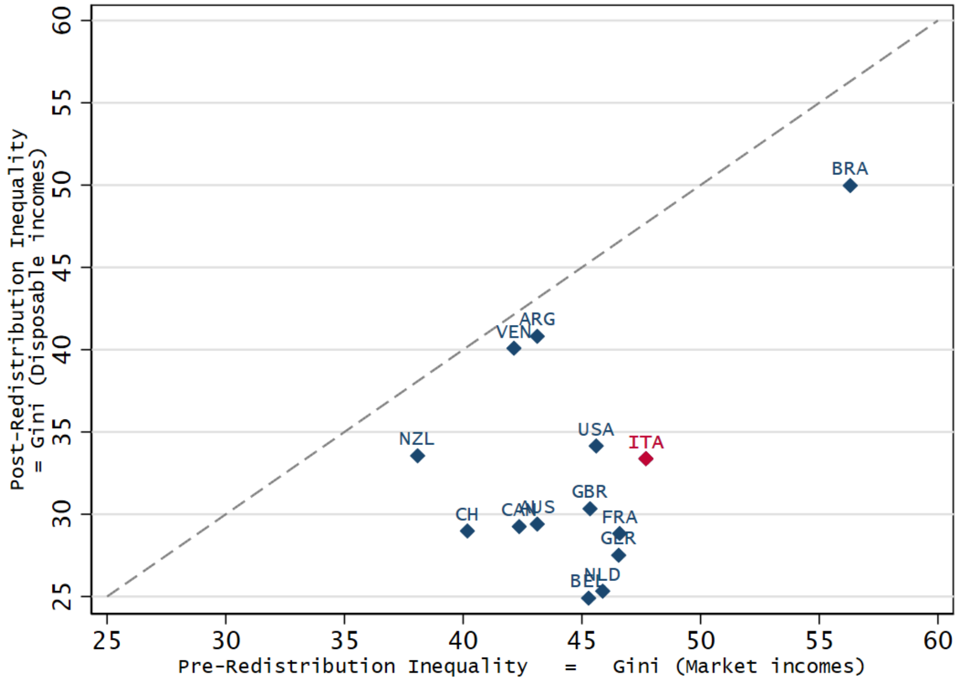
In most countries, the LIS does not contain a country-of-origin variable. In the few where it is available, the number of observations for (first generation) Italian immigrants is too low to provide consistent estimates. In principle, in most countries it would be possible to restrict the sample just to immigrants. However, without further specification, the ample heterogeneity within the group of immigrants leads to a very dispersed income distribution among this group in every country. Hence, we do not restrict the country-samples and assume that the (conditional) disposable incomes of Italian immigrants in the destination countries are not different from the incomes of natives and other immigrants with the same observable characteristics. To relax this assumption, in a further sensitivity analysis that is included in the Supplemental Material we adopt an alternative way to estimate net incomes, taking into account that the productivity associated with the level of education obtained by migrants in their source country might be different from the average productivity in the host country. There, we estimate the augmented Mincer regression on disposable household income with LIS data including a linear measure for years of schooling (instead of educational categories as in the main application). Then, we multiply the years of schooling of Italian migrants with a factor that measures the relative quality of the Italian education system with respect to the respective host country; we take this measure, based on PISA scores, from Razin and Wahba (2015). Finally, we estimate the net incomes, as before, using the coefficients of the Mincer regression.

For our main empirical exercise we use total yearly household income after taxes and transfers. Results that make use of an equivalence scale can be found in the Supplemental Material, and are similar to those presented in the main text.

3.3 Country characteristics

We collect data on country characteristics from the following sources: the Standardized World Income Inequality Database (SWIID), the World Income Inequality Database (WIID), World Bank Macro Data (WB-Data), and the Andrew Young School World Tax Indicators (WTI). From the SWIID we retrieve net and market income inequality indices and compute measures for absolute and relative redistribution, the first one measured by the difference between the market and net Gini index, the second one by this difference divided by the market Gini (see Reynolds and Smolensky, 1977; Solt, 2016). Since the heterogeneity in the degree of redistribution is the driving force in the theoretical model, we now illustrate this heterogeneity in the data. Figure 4 shows the average level of pre and post-redistribution inequality for all countries in our sample. The vertical distance from the 45 degree line shows the mechanical contribution (in Gini points) of taxes and transfers to the reduction of market income inequality. In Figure 5, on the vertical axis redistribution is defined in absolute terms while on the horizontal axis it is defined in relative terms. The Figure shows that countries rank in a similar way according to each definition of redistribution. Three groups of countries can be identified, with, respectively, a high, medium and low level of income redistribution. The first group comprises Belgium, the Netherlands, Germany and France. The second includes Italy, Great-Britain, Australia, Switzerland, Canada, and the US. The third is formed by

Figure 4: Levels of Inequality Pre- and Post-Redistribution

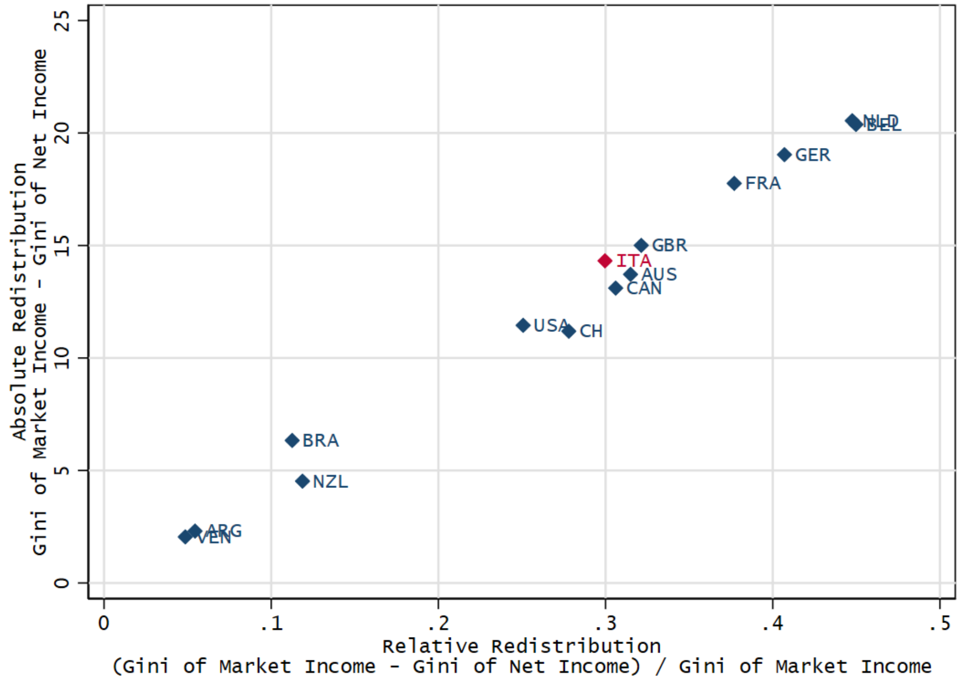


Source: SWIID, own calculations. Average over all available years.

New-Zealand, Brazil, Venezuela, and Argentina. Figure 6 shows the time trends in the evolution of governmental redistribution of income in each destination country, as compared to Italy.

To cross-check the results obtained using SWIID we have performed the same type of analysis using WIID, and obtained similar results. The latter is a dataset with less observations for each country than the former, but has been argued in the past to rely on a more consistent methodology than SWIID (see Jenkins, 2015). For the countries in our sample, including Italy, we find a very high degree of congruence between SWIID and WIID data, with a correlation of about 0.95. From the WTI data we retrieve a measure for the Marginal Tax Rate Progression and thus also run all the tests with this alternative measure; the results confirm the main analysis and are included in the Supplemental Material.

Figure 5: Absolute and relative redistribution



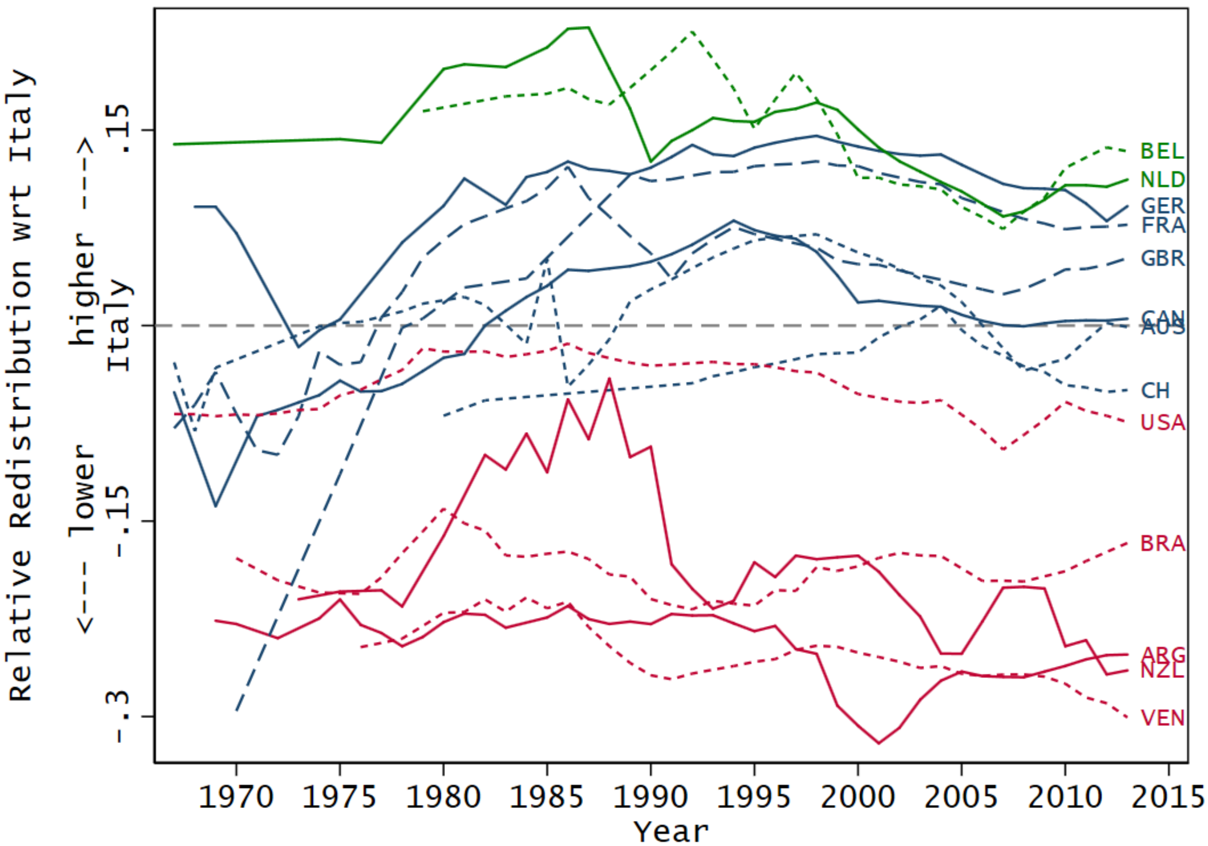
Source: SWIID, own calculations. Average over all available years.

4 Redistribution and Migration: Preliminary Evidence

According to the theory, migration choices are driven by the post-fisc value of human capital that individuals can achieve in the available countries, net of migration costs. Governmental redistribution of income in every country affects the valorization of human capital in such a way that individuals with a low level of pre-fisc human capital tend to have an incentive to migrate to countries with more redistribution, whereas individuals with a high level of pre-fisc human capital tend to have an incentive to migrate to countries with less redistribution. We now scrutinize this prediction in light of our data on migration from Italy since 1960.

The data we collected allow us to capture the concept of pre-fisc human capital in two different ways, for each of which a separate assessment of the theory is in order. The most straightforward way to capture an individual's human capital in our data is to proxy it by the individual's level of education. As mentioned above, the assessment of self-selection often depends on the definition

Figure 6: Redistribution trends with respect to Italy



Source: SWIID, own calculations.

of the reference population. Spitzer and Zimran (2018) analyse self-selection in stature of Italians that migrated to the US between 1907 and 1925. Their findings show that Italian immigrants were negatively selected with respect to the Italian national average height, but positively selected among their province of origin. This highlights the importance of evaluating selection patterns with respect to the correct reference group, for instance, at the sub-national level. Indeed, simple educational attainment misses potentially major variations in human capital that stem from variations in the quality of one year of education both over time and across space. An individual's human capital, her long-run potential to earn income in the various destination countries, may therefore be better captured by the relative educational achievement of the individual.

This is the first way in which we bring the theory to the data. We define the relative educational position of individual i born in year b as the relative difference of her years of education e with respect to the average of stayers born in the same year and residing in her Italian region of origin j:

$$s^e_{ijb} = \frac{e_{ijb} - \overline{e}_{jb}}{\overline{e}_{jb}}. \tag{4}$$

Values of this variable higher than zero represent positive selection on education, i.e. migrants are more educated than the average of their reference group, while negative values correspond to negative selection.

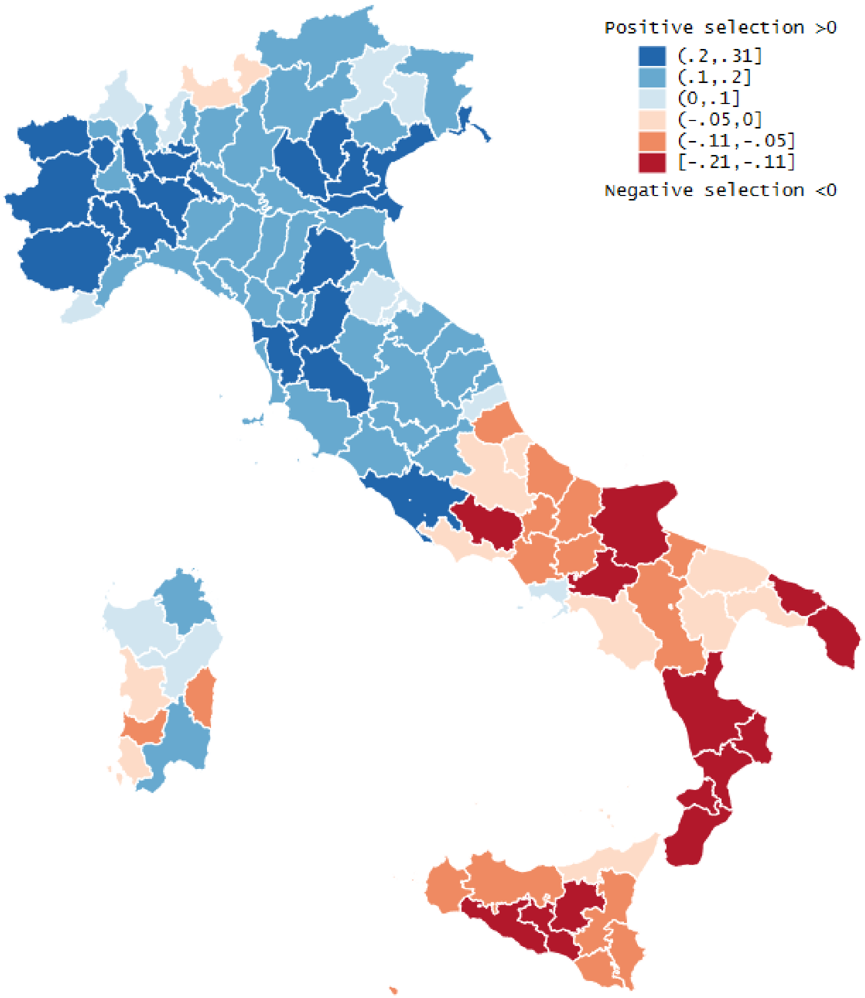
Figure 7 shows a map of Italy that displays the average relative educational position of Italians registered in AIRE by their province of origin. People in Southern Italy have, on average, lower levels of education than people in the North, and this pattern also applies to the migrants from those areas. The Figure reveals that migrants from the North tend to be positively selected among the population in that area, whereas migrants from the South of Italy are negatively selected. This pattern holds irrespective of the time of migration, although over time the overall degree of selection has progressively shifted towards a more positive one for most regions. Some significant variations with respect to destination countries are displayed in Figure 8. Italian migrants to Brazil, New Zealand, and Venezuela exhibit positive selection, independently of their time of arrival. Quite the opposite holds in the case of Germany, where only in recent years Italian migrants are positively selected.

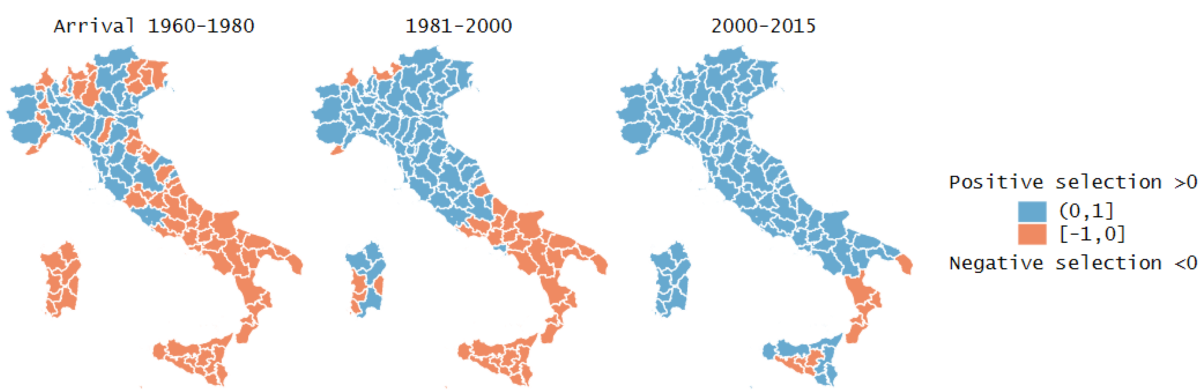
The relationship between redistribution and the relative education of Italian migrants is illustrated in Figure 9. The amount of redistribution is computed as the average relative redistribution over all available years in SWIID. This is plotted against the average relative educational position of Italian emigrants residing in the same country. The population weighted correlation is -0.38.

The second way in which pre-fisc human capital can be captured in our data is by the individuals' expected yearly earnings. As explained in the previous Section, no earnings information is included in the AIRE dataset and we use the SHIW of the Bank of Italy to predict migrants' counterfactual earnings in Italy. A drawback of yearly earnings as a measure of human capital is the low statistical association between yearly earnings and lifetime earnings at the beginning and at the end of the life-cycle. In order to avoid the corresponding bias, here we restrict our attention to individuals in the age-range 35 to 55. As shown by Bönke et al. (2015), yearly earnings in that part of the life-cycle are strongly correlated with permanent earnings.

Figure 10 depicts the relation between redistribution and earnings. The population weighted correlation is -0.65. If we replace the average relative distribution retrieved from SWIID with the Marginal Tax Rate Progression retrieved from the World Tax Indicators Data (WTI), the population weighted correlations with counterfactual earnings and relative educational position of Italian immigrants are -0.75 and -0.58, respectively. In sum, independently of the proxy for human capital and redistribution we employ, the preliminary evidence discussed in this section corroborates the notion that countries with a more progressive redistributive system negatively select their immigrants from Italy.

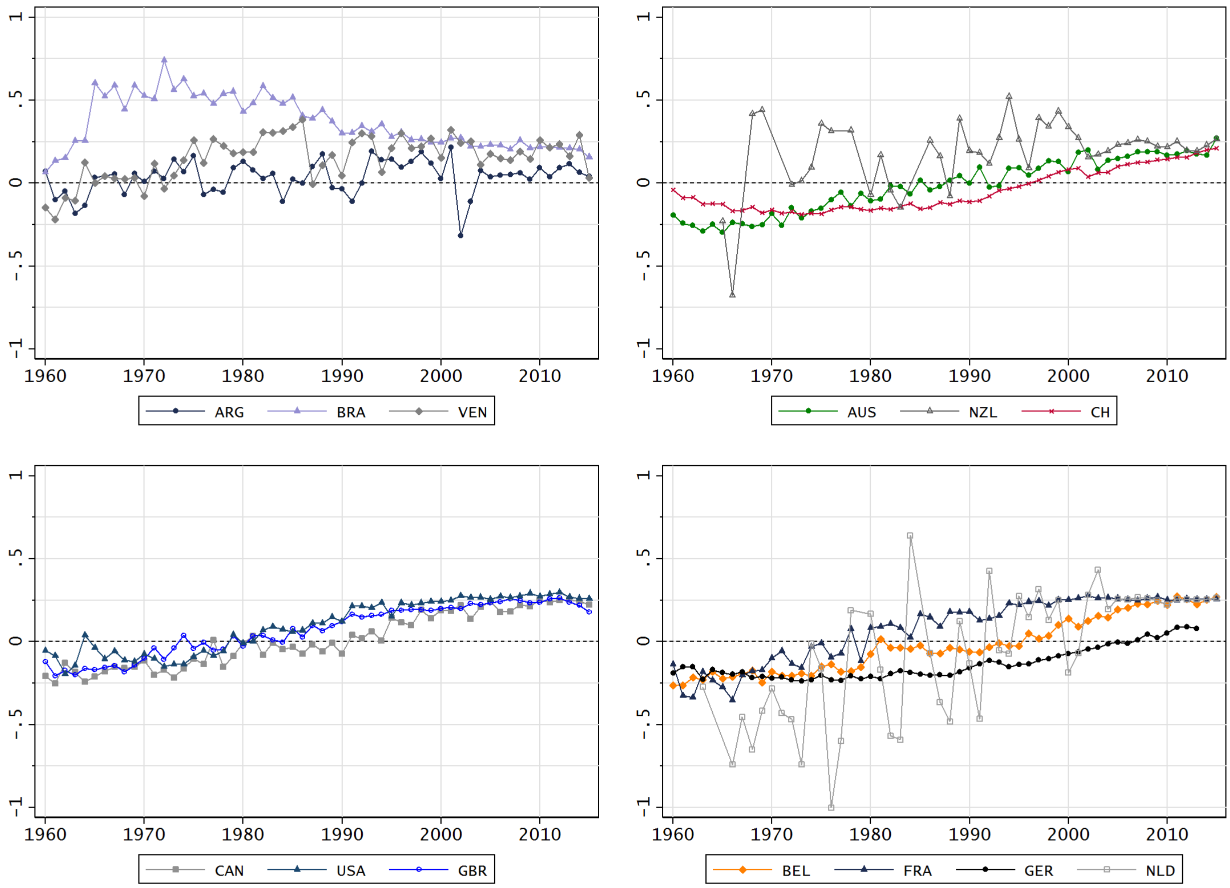
Figure 7: Relative educational position of Italian Mover by their province of origin.





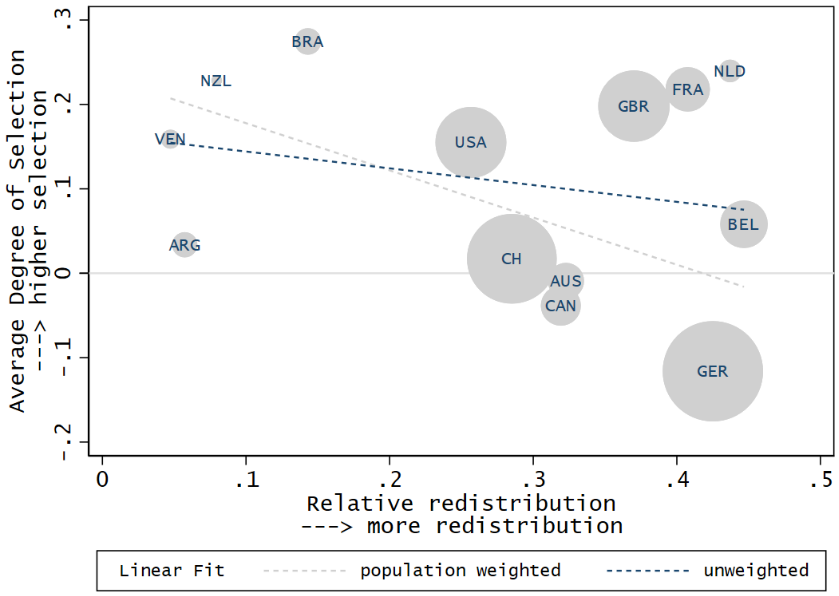
Notes: Maps show the province level average of relative educational position of all individuals in our AIRE sample. The individual relative educational position is estimated with respect to the population of stayer born in the same year and residing in the region of origin. Averages for Stayer are own calculations using SHIW.

Figure 8: Average Relative Educational Position of Italian Mover by Year of Arrival and Country of Residence



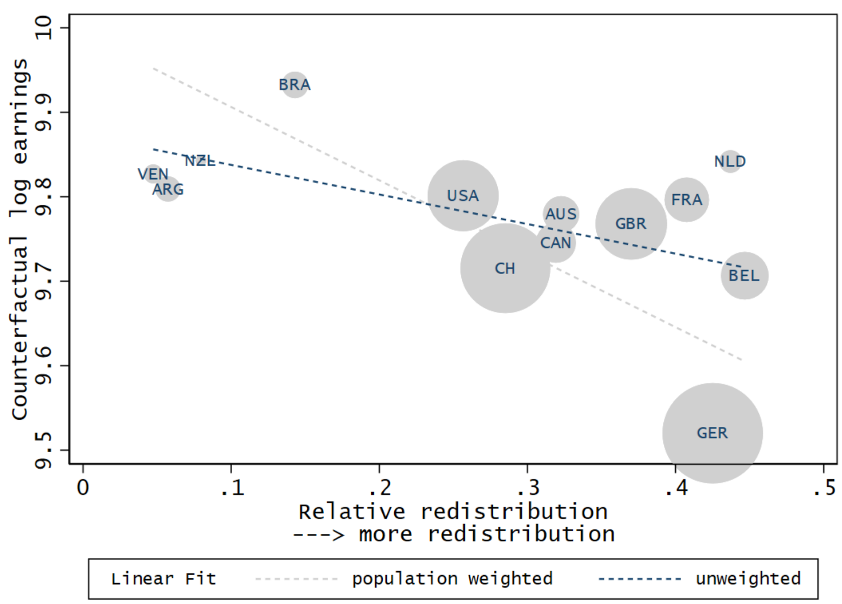
Notes: Relative educational position computed with respect to stayer born in the same year and resident in the region of origin. A value of zero is equivalent to the average of the reference group, values lower than zero show a negative selection, and values higher than zero a positive selection, on average. Source: AIRE, own estimates. Regional averages for every birth cohort are estimated using SHIW.

Figure 9: Returns to skills and self-selection of immigrants - Relative Educational Position



Notes: All variables are averages over the complete observation period. Sample are Italian immigrants aged 30-75. Sources: AIRE, SWIID, own calculations.

Figure 10: Returns to skills and self-selection of immigrants - Counterfactual earnings



Notes: All variables are averages over the complete observation period. Sample are Italian immigrants aged 35-55. Sources: AIRE, SWIID, own calculations.

5 Redistribution and degree of self-selection

5.1 Selection on observable skills

Are the insights derived from the previous Section robust to the inclusion of more information about how redistribution has changed over time, and across countries? To reach deeper into the association between the level of redistribution and the self-selection of migrants, we run the following linear regression:

$$s^*_{ijtc} = \alpha + \beta R_{tc} + \delta' Z_{tc} + \gamma' X_{ijtc} + \zeta' M_c + \lambda_j + \tau_t + \varphi_c + \varepsilon_{ijtc}, \tag{5}$$

where s^*_{ijtc} is the skill level of individual i from the Italian region of origin j who registered in year t to the registry of Italians living abroad in country c, either measured by the relative educational position or by the predicted counterfactual log labour earnings that i would have obtained had he stayed in Italy. The regression equation relates this measure of skill to R_{tc}, the average level of relative redistribution in country c in all years from t to the last year of the data (2015). Since t is usually the year of arrival of the migrant in the destination country, this definition of redistribution captures the effect of the tax-transfer-system on the entire income stream received by the migrant in that country.[8]

The same procedure is applied to other macroeconomic variables that are included in Z_{tc}. This vector of controls includes the unemployment rate, the growth rate of GDP, and the level of GDP per capita. These variables are indicators that may shape the income expectations of individuals that are potentially willing to migrate. X_{ijtc} is a vector of controls for individual characteristics: year of birth (polynomial of second degree), sex, Italian region of origin, month of birth, year of arrival of the first immigrated member of the household, and dummies indicating whether the individual has a prior internal migration experience, was the first household member to arrive in the country of destination, rural or urban location of origin (definition: < 150 inhabitants/km^2), and

[8] Regressions that employ the level of redistribution only in the year of arrival yield similar results and are included in the Supplemental Material.

if the individual lives in the capital of the host country.[9] M_c is a vector of controls for non-varying country characteristics that act as proxies for the costs of migrating to a particular country. It includes the distance from the Italian border, a dummy that equals 1 if this country and Italy signed an immigration agreement, and the share of migrants from the same Italian province residing in that particular country. λ_j, τ_t and φ_c are fixed effects for the Italian region of origin, the year of arrival, and the country of destination. Standard errors are clustered at the country-year level.

Table 4 and Table 5 show the results of estimating equation (5) for our two definitions of skills on the sample of Italian immigrants worldwide. The coefficient of the variable that indicates the relative level of redistribution in the country of destination is negative, and highly significant in all but one specification of the model. An increase of relative redistribution by 10 percentage points is associated with a decrease in the degree of self-selection of Italian migrants of between 4 and 9 percent. These findings corroborate the insight suggested by the descriptive evidence in the previous Section; less egalitarian countries attract migrants with higher skills than those attracted by egalitarian countries. Furthermore, the results hold for both measures of skills, relative education and earnings, as well as when we perform the analysis separately for men and women, for each Italian macro-region of origin, and only for those Italian migrants from provinces with at least 10,000 emigrants. Further results of the regressions which include inequality, as well as measuring redistribution by the coefficient of residual progression or the marginal tax rate progression with alternative measurements and datasets, yield the same patterns, and can be found in the Supplemental Material.

Interestingly, two variables that capture so-called network effects show the expected negative relationship with the selectivity of migrants. Past research argued that networks lower the cost of migration with a gradient, making it more attractive for low-skilled individuals to migrate, and hence lowering, on average, the pattern of positive self-selection of particular immigrant groups (e.g. Mckenzie and Rapoport, 2007; McKenzie and Rapoport, 2010). Our results confirm those findings. The presence of people from the same province of origin is negatively and significantly

[9]When the skill level is measured using earnings as dependent variable, only control variables are included in the regression that have not been used for the prediction of these earnings.

Table 4: Redistribution and degree of selection: Education

	(1)	(2)	(3)	(4)
Relative Redistribution	-0.476***	-0.463***	-0.503***	-0.870***
	(0.0982)	(0.0643)	(0.0676)	(0.319)
Network size (province of origin)		-0.422***	-0.411***	-0.317***
		(0.0143)	(0.0142)	(0.0115)
Other family members migrated earlier (0/1)		-0.0449***	-0.0431***	-0.0392***
		(0.00444)	(0.00431)	(0.00428)
Female (0/1)		0.0103***	0.00956**	0.00963**
		(0.00385)	(0.00386)	(0.00374)
Rural place of origin (0/1)		-0.0576***	-0.0566***	-0.0539***
		(0.00280)	(0.00277)	(0.00277)
Internal migration experience before emigration (0/1)		-0.0235***	-0.0228***	-0.0204***
		(0.00354)	(0.00351)	(0.00342)
Resident in the capital (0/1)		0.106***	0.103***	0.0872***
		(0.00624)	(0.00636)	(0.00622)
Distance of country of residence from Italian border (in 1000 km)		-0.00293***	-0.00540***	
		(0.000760)	(0.00111)	
Migration agreement between Italy and country of residence (0/1)		-0.0843***	-0.0733***	
		(0.00689)	(0.00777)	
Migration policies oriented towards high skilled (0/1)		-0.0200**	0.00428	
		(0.00867)	(0.00973)	
Unemployment rate			0.0118***	-0.00604*
			(0.00188)	(0.00308)
GDP growth			0.00630	-0.00614
			(0.00587)	(0.00810)
GDP per capita			-0.0000579	0.00516***
			(0.000209)	(0.000642)
Constant	0.199***	-64.89	-82.25	-29.21
	(0.0323)	(50.17)	(50.45)	(49.41)
Demographic controls	No	Yes	Yes	Yes
Country F.E.	No	No	No	Yes
Observations	296758	292056	292056	293584
R^2	0.011	0.246	0.248	0.253

Notes: Sample are Italian immigrants aged 30-75. Dependent variable in the regressions is the relative educational position as individual measure of relative skills. Demographic controls include year of birth (polynomial of second degree), sex, Italian region of origin, month of birth, year of arrival of the individual and of the first immigrated member of the same household, a dummy indicating whether the individual was the first household member to arrive in the country of destination, rural or urban location of origin (definition: < 150 inhabitants/km2). Standard errors clustered at the country-year level. Statistical significance level * 0.1 ** 0.05 *** 0.01. Source: AIRE, own estimations.

Table 5: Redistribution and degree of selection: Earnings

	(1)	(2)	(3)	(4)
Relative Redistribution	-0.918***	-0.704***	-0.836***	-0.398
	(0.111)	(0.0654)	(0.0705)	(0.336)
Network size (province of origin)		-0.347***	-0.333***	-0.259***
		(0.0475)	(0.0472)	(0.0536)
Other family members migrated earlier (0/1)		-0.198***	-0.196***	-0.193***
		(0.00926)	(0.00906)	(0.00902)
Rural place of origin (0/1)		-0.120***	-0.119***	-0.115***
		(0.00653)	(0.00640)	(0.00619)
Resident in the capital (0/1)		0.0814***	0.0782***	0.0652***
		(0.00517)	(0.00521)	(0.00496)
Distance of country of residence from Italian border (in 1000 km)		0.00130	-0.00117	
		(0.000865)	(0.00108)	
Migration agreement between Italy and country of residence (0/1)		0.00728	0.0223***	
		(0.00687)	(0.00752)	
Migration policies oriented towards high skilled (0/1)		0.0155*	0.0217**	
		(0.00844)	(0.0102)	
Unemployment rate			0.0158***	-0.00136
			(0.00254)	(0.00311)
GDP growth			0.0194***	0.0203***
			(0.00701)	(0.00525)
GDP per capita			0.000565**	0.00462***
			(0.000223)	(0.000692)
Constant	10.02***	9.886***	9.757***	9.727***
	(0.0358)	(0.0539)	(0.0555)	(0.0534)
Demographic controls	No	Yes	Yes	Yes
Country F.E.	No	No	No	Yes
Observations	148729	148410	148410	148729
R^2	0.040	0.197	0.199	0.205

Notes: Sample are Italian immigrants aged 35-55. Dependent variable in the regressions is the predicted counterfactual log labour earnings in Italy as individual measure of relative skills. Demographic controls include month of birth, year of arrival of the individual and of the first immigrated member of the same household, a dummy indicating whether the individual was the first household member to arrive in the country of destination, rural or urban location of origin (definition: < 150 inhabitants/km2). Standard errors clustered at the country-year level. Statistical significance level * 0.1 ** 0.05 *** 0.01. Source: AIRE, own estimations.

associated with the skill level of migrants. Moreover, the presence of a family member in the country of residence is associated with a 4 and 20 percent lower degree of skill selection for education and earnings, respectively. Furthermore, we observe that Italian immigrants originating from rural areas have a lower degree of selection, while those residing in the capital of their country of destination are more likely to be positively selected.

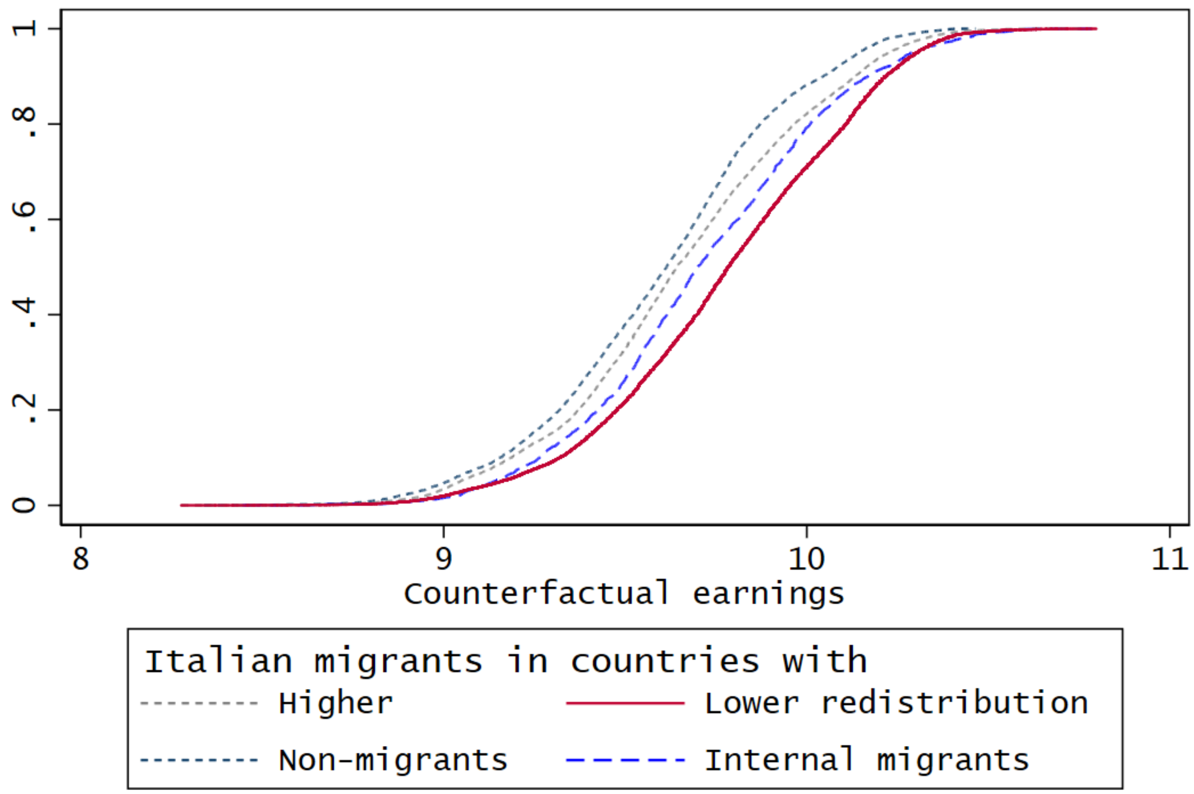
Among country characteristics, the distance of the country of destination from Italy is very weakly associated with selectivity. The same applies to the existence of a bilateral migration agreement between Italy and the country of destination. Unemployment, GDP growth, and GDP per capita in the country of destination tend to be positively associated with the degree of self-selection of Italian migrants.

5.2 Stochastic dominance

As discussed by Borjas et al. (2018), the Roy-Model of self-selection implies a first-order stochastic-dominance relationship between the skill distributions of movers and stayers. Investigating such a relationship can yield further insights into the role played by income redistribution in shaping migration patterns.

We now test for stochastic dominance with respect to the behavior of Italian migrants. As argued by Chiquiar and Hanson (2005), the complete group of stayers might not be a proper comparison group for movers because of the selection that occurs on unobserved characteristics that also affect the distribution of earnings. We thus subdivide the group of stayers into two separate groups: i) internal migrants, i.e. individuals that migrated within Italy between regions; ii) non-migrants, i.e. individuals that reside in their region of birth. Movers, i.e. individuals in the AIRE dataset, are divided into two groups according to the amount of redistribution they experienced in the country of destination in comparison to the extent of redistribution in Italy (again, measured as the average redistribution from the year of arrival to the last available year in the dataset): i) Italian migrants in countries with higher redistribution than in Italy; ii) Italian migrants in countries with

Figure 11: Cumulative distributions of counterfactual earnings



Notes: Counterfactual earnings of individuals have they stayed in Italy are log labor earnings predicted for all individuals in AIRE after running a Mincer-regression on SHIW data. Distributions for migrants are own estimations using AIRE. Distribution of non-migrant and internal migrants are own estimations using SHIW. Sample are individuals aged 35-55.

less redistribution than in Italy. Figure 11 plots the cumulative distributions of the corresponding skills, i.e. predicted earnings in Italy, of these four groups.

The results are consistent with the Roy-Model of self-selection. The skill distribution of migrants in countries with a low level of redistribution dominates the distributions of stayers and of migrants in countries with a high level of redistribution. At the same time, the skill distribution of migrants in countries with higher redistribution stochastically dominates the distribution of non-migrants, but is dominated by the distribution of internal migrants. A Kolmogorov-Smirnov test of equality of distributions shows that all of the differences between the distributions of the four groups visualized in Figure 11 are statistically significant.

5.3 Selection on unobservable skills

The variables we have hitherto employed to proxy for the individuals' human capital may fail to capture idiosyncratic abilities and motivations that affect the individuals'earnings potential, but cannot be directly observed by the researcher. To assess the relationship between redistribution and the selection on those unobservable skills, we now conduct two empirical investigations. The aim of each is to ascertain whether the likelihood to attain certain occupational positions changes with the level of redistribution, holding observable skills constant. We apply a Probit model on a binary variable indicating the occupation status h_{ijtc} of individual i who registered in year t to the registry of Italians living abroad in country c. We adopt two different specifications for h: in one specification, this variable equals 1 if the individual is unemployed or inactive, and 0 if the individual is employed; in the second specification, $h_{ijtc} = 1$ if the individual is an executive or manager, and $h_{ijtc} = 0$ if in another type of occupation or unemployed. The educational attainment of the individual, s^e_{ijtc}, is included in the equation as a binary variable that is 1 if the individual attained beyond compulsory education and 0 otherwise. Figure 12 highlights how the composition of Italians abroad varies across countries with respect to both educational attainment and occupation, and how this compares to those compositions in Italy.

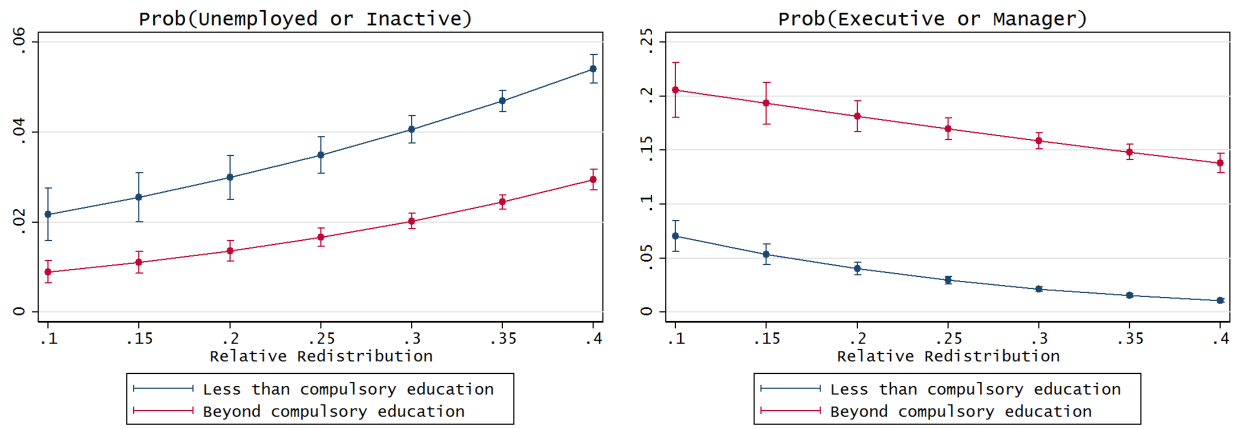
We estimate the following model:

$$Prob(h_{ijtc} = 1) = \Phi(\iota R_{tc} \cdot s^e_{ijtc} + \beta R_{tc} + \theta s^e_{ijtc} + \gamma' X_{ijtc} + \delta' Z_{tc}). \tag{6}$$

Individual-level covariates are included in X_{ijtc}, while country-level covariates appear in Z_{tc}. The marginal effect of the interaction term, determined through ι and computed at different values of R_{tc}, shows how the likelihood of being unemployed or of having a high occupational status (executive or manager) varies with redistribution for immigrants with high and low education, respectively. Because of the lower and less stable attachment of women to the labor market, as evidenced in Figure 12, we restrict the sample for this analysis to men.

Figure 12: Occupation and Education of Italian immigrants aged 30-65 by country

Figure 13: Selection on unobservable skills



Notes: Dots show the predicted probabilities for different levels of relative redistribution. Left figure shows the marginal effects of the interaction term in model (2) on Table 6, right figure shows the marginal effects of the interaction term in model (6).

Table 6 shows the estimated coefficients of the Probit models. In the first and third columns of both specifications of the dependent variable, the coefficient on the interaction term is restricted to be zero. The marginal effects of the interaction terms for different levels of relative redistribution are plotted in Figure 13. Again, our findings are in line with the hypothesis of the Roy-Model: there is a positive relationship between returns to skills and the self-selection of immigrants on unobservable characteristics. Controlling for education, redistribution is associated with an increased likelihood of being unemployed or inactive, and a lower likelihood of being an executive or manager. However, in the case of the latter dependent variable, once country fixed effects are included, the coefficient ceases to be significantly different from zero in both applications. The reason for this could be that the largest variation in the level of redistribution takes place between countries.

The evidence in favor of the Roy-Model is reinforced by looking at the likelihood of being in each of those states for individuals with different educational attainments. As is evident from the marginal effects displayed in in Figure 13, the likelihood of being unemployed is significantly lower for individuals with higher educational attainments. Interestingly, this likelihood increases, regardless of an individual's level of education, with increasing degrees of redistribution. The greater is the difference in the likelihood between levels of education, the higher is the level of

Table 6: Selection on unobservable skills

	Prob(Unemployed)				Prob(Executive or Manager)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Probit estimates								
Beyond compulsory education (0/1)	-0.299***	-0.380***	-0.288***	-0.415***	1.184***	0.507***	1.163***	0.657***
	(0.0193)	(0.0867)	(0.0192)	(0.0870)	(0.0237)	(0.0805)	(0.0233)	(0.0847)
Relative Redistribution	1.522***	1.416***	4.651***	4.513***	-1.284***	-3.015***	1.944	0.857
	(0.183)	(0.221)	(1.548)	(1.553)	(0.196)	(0.239)	(1.324)	(1.365)
Beyond compulsory · Relative Redistribution		0.223		0.352		2.041***		1.545***
		(0.225)		(0.229)		(0.246)		(0.270)
Share of people from the same province in country of residence	0.233***	0.242***	0.134**	0.139**	-0.771***	-0.740***	-0.469***	-0.462***
	(0.0573)	(0.0586)	(0.0676)	(0.0676)	(0.0620)	(0.0612)	(0.0635)	(0.0638)
Other family members migrated earlier (0/1)	0.0589*	0.0585*	0.0590*	0.0588*	-0.0661	-0.0689	-0.101**	-0.104**
	(0.0318)	(0.0318)	(0.0318)	(0.0319)	(0.0456)	(0.0456)	(0.0452)	(0.0453)
Rural place of origin (0/1)	-0.0752***	-0.0754***	-0.0815***	-0.0817***	-0.192***	-0.194***	-0.185***	-0.186***
	(0.0165)	(0.0165)	(0.0166)	(0.0166)	(0.0179)	(0.0180)	(0.0181)	(0.0181)
Internal migration experience before emigration (0/1)	0.0178	0.0180	0.0151	0.0152	0.0727***	0.0739***	0.0761***	0.0769***
	(0.0232)	(0.0232)	(0.0235)	(0.0235)	(0.0158)	(0.0158)	(0.0159)	(0.0160)
Resident in the capital (0/1)	-0.0450	-0.0483	-0.0166	-0.0192	0.0389	0.0253	0.118***	0.111***
	(0.0363)	(0.0367)	(0.0384)	(0.0385)	(0.0247)	(0.0247)	(0.0241)	(0.0241)
Unemployment rate	-0.0340***	-0.0332***	0.00630	0.00720	0.0669***	0.0682***	-0.00495	-0.00185
	(0.0115)	(0.0115)	(0.0160)	(0.0161)	(0.0122)	(0.0122)	(0.0130)	(0.0131)
GDP growth	-0.0137	-0.0133	-0.0183	-0.0185	-0.109***	-0.106***	0.00377	0.00236
	(0.0210)	(0.0212)	(0.0238)	(0.0241)	(0.0294)	(0.0296)	(0.0250)	(0.0251)
GDP per capita	-0.0113***	-0.0114***	-0.0125***	-0.0117***	0.00573***	0.00571***	-0.00490	-0.00325
	(0.00112)	(0.00118)	(0.00328)	(0.00334)	(0.00154)	(0.00154)	(0.00336)	(0.00340)
Constant	33.09***	33.17***	32.93***	33.06***	60.01***	61.01***	58.67***	59.45***
	(2.768)	(2.783)	(2.762)	(2.777)	(2.717)	(2.797)	(2.783)	(2.848)
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country F.E.	No	No	Yes	Yes	No	No	Yes	Yes
Observations	106214	106214	106214	106214	106137	106137	106137	106137
Pseudo R^2	0.056	0.057	0.060	0.060	0.234	0.235	0.250	0.251

Notes: Dependent variable in columns (1) to (4) is one if the individual is unemployed or inactive, and zero if in an employment situation. Dependent variable in columns (5) to (8) is one if the individual is an executive or manager, and zero if unemployed or in another type of occupation. Demographic controls include year of birth, year of arrival, italian region of origin, a dummy indicating whether the individual was the first household member to arrive in the country of destination, rural or urban location of origin (definition: < 150 inhabitants/km2), and dummy variables indicating if the individual has an internal migration experience prior to emigration and if he or she lives in the capital of the host country. Standard errors clustered at the country-year level. Sample are Italian immigrants aged 30-65. Statistical significance level * 0.1 ** 0.05 *** 0.01. Source: AIRE, own estimations.

redistribution. The same pattern is observed for the likelihood of being an executive or a manager. Particularly among individuals with higher educational levels, the likelihood of being an executive or a manager is substantially higher when the level of redistribution is low.

6 Quantifying the Effect of Monetary Returns on Migration

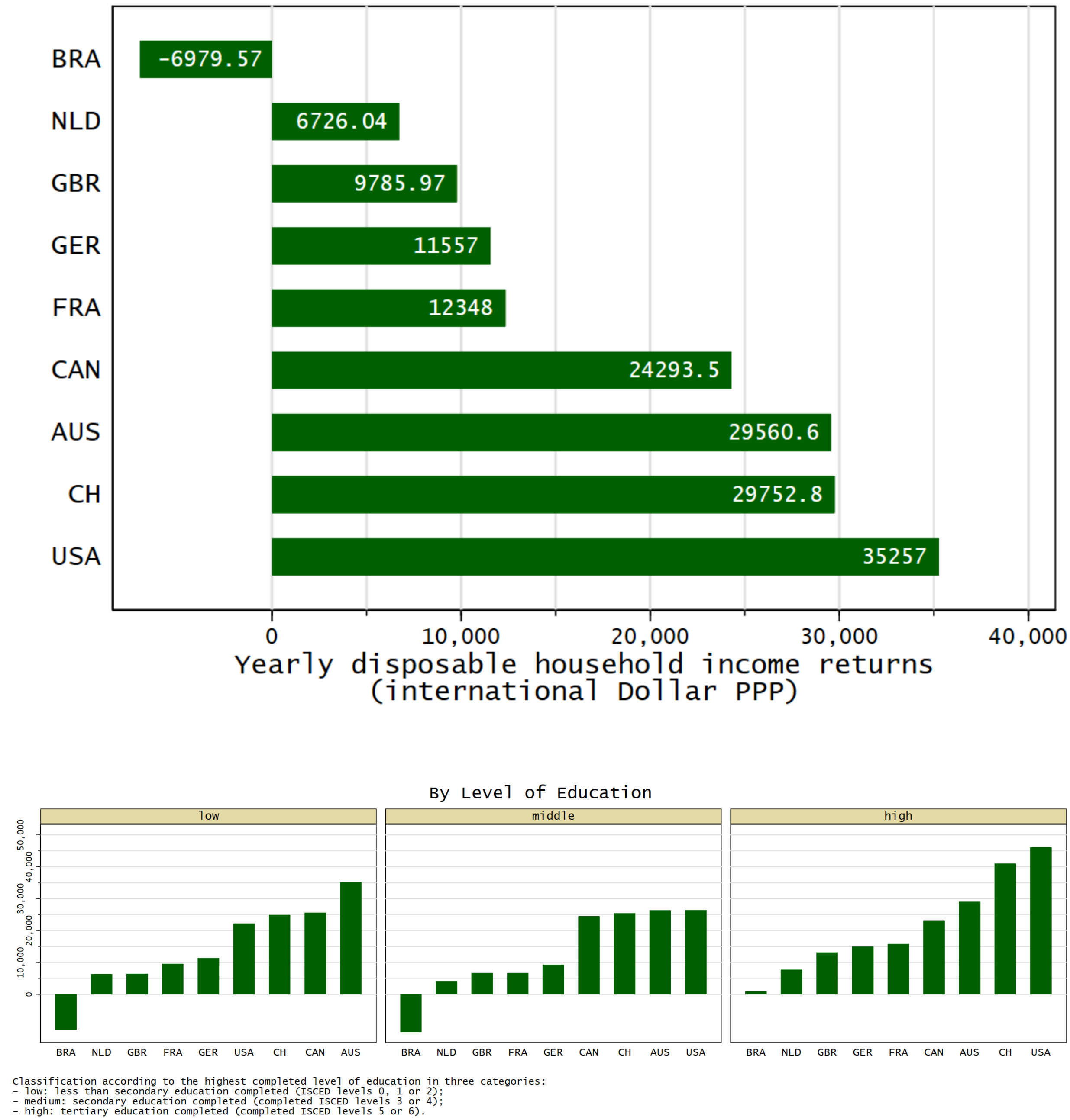
6.1 International income differentials

After having ascertained the empirical relevance of governmental income redistribution in shaping migration patterns, we now turn to a quantification of the pecuniary incentives to migrate, and of the impact of redistributive policies. As described in Section 3, for four countries there are no comparable national surveys that can be combined with the AIRE dataset in order to predict post-fisc incomes; the entire analysis in this Section is therefore restricted to nine countries. For those available countries, Figure 14 shows the average net returns to migration to the actually chosen country, estimated with LIS data for the Italian migrants in our sample. Net returns are defined as the difference between the predicted yearly disposable household incomes (net of taxes and transfers) in the country of destination and the counterfactual disposable income in Italy.[10] The age-range of the population is 35-55. All values are in international US-Dollars using purchasing power parity at 2011 prices.

Estimated monetary returns reach almost 4,000 USD per month in the case of highly-educated Italians who migrated to the US. Of course, such large income differences do not allow one to infer correspondingly large differences in living standards or well-being, in particular because of substantial cross-country differences with respect to the public provision of education, health care, child and old-age care, and retirement income. Net returns of Italian migrants to the four EU countries in our sample, with welfare-state arrangements that are more similar to those in Italy, are in a range between about 600 and 1,000 USD PPP per month. Migration to Brazil generates

[10] We also estimate the returns in terms of equivalized household income (using the square root scale) and report the results in the Supplemental Material. However, since the decision on family formation and number of children might be endogenous to the migration decision and the choice of the host country, in our main applications we rely on the total household disposable income to measure the net returns to migration.

Figure 14: Predicted monetary returns to migration



Notes: The coefficients used to predict the net incomes and counterfactual net incomes of immigrants in AIRE are estimated using LIS data, running an augmented Mincer regression for each single country on disposable household income including the variables sex, age, quadratic age, education, and an indicator on whether at least one child lives in the household. Disposable incomes (in international US Dollars applying Purchasing Power Parity) of Italian immigrants and their counterfactual in Italy are predicted using the coefficients of this regression. Returns to migration are then defined as the difference between predicted incomes in the destination country and the counterfactual income in Italy. Source: AIRE and LIS, own estimates.

positive monetary returns only for highly-educated migrants, suggesting that negative migration costs may be empirically relevant for some individuals in some countries.[11]

6.2 Migration choice

We now estimate a discrete-choice model of the decision to migrate as a function of the net incomes that can be obtained in Italy and the potential destination countries, taking personal characteristics and place characteristics of the countries of destination into account. Models of this type are usually applied to estimate the determinants of the migration decision (e.g. Davies et al., 2001; O'Keefe, 2004; Vigdor, 2002). A similar set-up has been adopted, for instance, by Grogger and Hanson (2011) on aggregate data to test the selection of international migrants.

We pool our administrative data on Italian migrants with the Italian survey data on stayers and run an alternative-specific conditional logit model (McFadden, 1974). The explanatory variables are either alternative-specific or case-specific. The former vary among countries and individuals, while the latter vary only among individuals. The model is motivated by a random utility framework, which has the potential utility of migrant i in country $c = 1, ..., C$ as a function of the obtainable net income in that country and other country variables. Such an income varies for each individual depending on his or her level of education and other individual characteristics, as well as some other country-specific characteristics that may vary for each individual depending on his or her year of migration. The model can be expressed as

$$U_{ic} = \gamma' Z_{ic} + \alpha_c' A_{ic} + \varepsilon_{ic}, \tag{7}$$

where U_{ic} is the utility derived from the potential choice of each alternative country of destination, including the decision to stay in Italy. The country actually chosen by i is the one that is expected

[11] As explained above, we perform a sensitivity analysis taking into account that education systems are of different quality and, hence, migrants that acquired their education in their source country have a different productivity level than the average of the host country's population. We follow the procedure proposed by Razin and Wahba (2015) and use their estimates for educational quality based on PISA test scores to correct for the quality of education systems between source and host country. All these estimations results, and an exhaustive explanation of the procedure, can be found in the Supplemental Material.

to maximize his or her utility. The vector Z_{ic} includes the individual's net income in the various countries as well as other alternative-specific characteristics. A_{ic} is a vector that contains dummy variables for each country and individual specific characteristics that do not change across alternatives. These are interacted with each potential choice, yielding coefficients α_c for each potential country of destination. Hereby, we must set one of the countries as the baseline alternative, setting $\alpha_k = 0$ for this baseline country k. We set Italy – i.e. the choice to stay – as baseline when the full decision set is evaluated, and Switzerland when the regression is run just on the sample of movers only. ε_{ic} is the random component, which is assumed to be independently and identically distributed with an extreme-value distribution. Under this assumption the probability that i chooses destination country c is

$$Prob(D_{ic} = 1) = \frac{e^{\gamma' Z_{ic} + \alpha_c' A_{ic}}}{\sum_{j=1}^{C} e^{\gamma' Z_{ij} + \alpha_c' A_{ij}}}, \tag{8}$$

where D_{ic} is an indicator of i's decision regarding the country of destination. Each individual chooses among the 10 countries in the choice set, including Italy. Hence, the dataset is expanded to encompass 10 observations for each individual where D_{ic} is equal to one if c is i's actual country of residence and zero otherwise.

Z captures the circumstances the individual faces in the actual country of residence and that he or she would face in the other potential destinations, for instance, the different amounts of disposable household income. Individual level control variables included in A are indicators for age, sex and the Italian geographic region of origin. The model is estimated on the whole sample, as well as separately for each education group. Population weights are applied.[12]

Table 7 shows the estimated coefficients of the conditional logit model including only predicted disposable income as alternative-specific variable and the associated marginal effects of net income returns on the choice of the country of destination; the first part of the Table includes Italy in the choice set, the second one excludes it. The estimated coefficient on predicted net income is always

[12] As before, for SHIW we use the data design weights and for AIRE we compute weights that counterbalance the observations with missing information on educational attainment.

Table 7: Conditional Logit Estimates I

	w/ Italy				w/o Italy			
Education Level	All	Low	Middle	High	All	Low	Middle	High
Choice: Destination Country								
Predicted Net Income (absolute)	0.967***	1.071***	1.046***	1.098***	0.198***	0.0736***	0.0917***	0.0429***
	(0.0300)	(0.0481)	(0.0466)	(0.0772)	(0.00588)	(0.0192)	(0.0147)	(0.0146)
Log-lik.	-1280992.5	-452687.2	-386660.9	-412886.2	-333002.3	-94932.3	-98838.1	-123278.8
Observations	1519960	558070	437330	524560	1326195	481896	378963	465336
Cases	151996	55807	43733	52456	147355	53544	42107	51704
Alternatives	10	10	10	10	9	9	9	9

	ITA	AUS	BRA	CAN	CH	FRA	GBR	GER	NLD	USA
Population Shares	98.820	0.030	0.020	0.030	0.270	0.080	0.230	0.350	0.020	0.170
Predicted Probabilities	98.855	0.027	0.020	0.025	0.257	0.075	0.226	0.334	0.017	0.163
Marginal effect·100 : w/ Italy / w/o Italy										
Low Education	0.51 / -	0.01 / 0.12	0.00 / 0.04	0.01 / 0.12	0.09 / 1.41	0.02 / 0.16	0.06 / 0.52	0.27 / 1.83	0.00 / 0.02	0.04 / 0.48
High Education	1.76 / -	0.04 / 0.10	0.03 / 0.07	0.04 / 0.09	0.23 / 0.66	0.21 / 0.41	0.58 / 0.86	0.23 / 0.52	0.04 / 0.10	0.38 / 0.68

Notes: Upper Table shows the coefficients of the alternative specific conditional logit model. The model estimates the probability to stay in Italy or chose one of the 9 destination countries as a function of predicted net income returns to migration. Controls for age, sex and the Italian geographic region of origin are included. Standard errors clustered at the individual level. Sample are Italian immigrants and stayer aged 35-55. Statistical significance level * 0.1 ** 0.05 *** 0.01. Lower Table shows the actual population shares and the predicted probabilities using the estimated parameters of the model, as well as the marginal effects (multiplied by 100) of a yearly net income rise by 10,000 international USD PPP in the country on the probability to stay/migrate in/to this country. Source: AIRE and SHIW, own estimations.

positive and highly significant. This pattern also holds when excluding Italy from the possible choices, and hence focusing on the population of migrants.[13] The marginal effects show that a yearly net income increase of 10,000 international Dollars PPP in Italy increases the probability of less and highly educated individuals of staying in Italy by around 0.5 and 2 percent, respectively. To give another example, the average yearly returns to migration of less educated Italian immigrants in Switzerland, 25,000 USD, are associated to a higher likelihood by 3.5 percent to move to Switzerland instead of to another possible destination country.

[13]The patterns of the results do not change when net incomes are estimated taking into account the relative quality of education systems in source and host country, and when household disposable income is equivalized by the square root scale. In some of the estimations taking equivalized income within education groups the coefficients change or are statistically not significant. However, within education groups this income measure has very little variability. Furthermore, as explained above, because of the endogeneous relationship between the number of household components and the migration decision, we mostly rely on the total household disposable income as main measure for net returns to migration.

Table 8: Conditional Logit Estimates II

	w/o Country FE				w/ Country FE			
Education Level	All	Low	Middle	High	All	Low	Middle	High
Choice: Destination Country								
Predicted Net Income (absolute)	0.140***	0.132***	0.188***	0.0666***	0.129***	0.0890***	0.107***	0.0676***
	(0.00592)	(0.0200)	(0.0156)	(0.0147)	(0.00604)	(0.0200)	(0.0154)	(0.0149)
Share of migrants from the same province of origin	4.528***	5.227***	3.952***	2.368***	4.598***	5.246***	4.063***	2.416***
	(0.0271)	(0.0464)	(0.0502)	(0.0566)	(0.0274)	(0.0466)	(0.0508)	(0.0568)
Distance of country of residence from Italian border (in 1000 km)	-0.000265***	-0.000410***	-0.000332***	-0.000413***				
	(0.00000801)	(0.0000174)	(0.0000143)	(0.0000141)				
Language relatedness	0.0338***	0.0394***	0.0472***	0.0548***				
	(0.00121)	(0.00228)	(0.00222)	(0.00228)				
Unemployment rate	0.207***	0.113***	0.0968***	0.185***	0.157***	0.110***	0.0670***	0.147***
	(0.00425)	(0.00962)	(0.00822)	(0.00716)	(0.00463)	(0.0101)	(0.00889)	(0.00796)
GDP per capita	0.0208***	0.0263***	0.0480***	0.0444***	0.0372***	0.0305***	0.0642***	0.0607***
	(0.000841)	(0.00195)	(0.00153)	(0.00147)	(0.00105)	(0.00220)	(0.00182)	(0.00189)
Log-lik.	-313578.3	-84191.8	-94663.3	-121661.6	-310441.4	-83915.7	-93541.1	-121069.4
Observations	1322106	481142	377514	463450	1322106	481142	377514	463450
Cases	147187	53497	42034	51656	147187	53497	42034	51656
Alternatives	9	9	9	9	9	9	9	9

Notes: Probability to chose one of the 9 destination countries as a function of predicted net income returns to migration and other country characteristics. Controls for age, sex and the Italian geographic region of origin are included. Sample are Italian immigrants aged 35-55. Standard errors clustered at the individual level. Statistical significance level * 0.1 ** 0.05 *** 0.01. Source: AIRE, own estimations.

Table 8 shows the estimated coefficients of the conditional logit model, including the full set of alternative-specific control variables and excluding Italy as a possible destination. The coefficient on net income is positive and significant. Furthermore, the probability of choosing one country over another is positively associated with language relatedness and GDP per capita, and negatively with the distance of the country from the Italian border.[14] Against the expectations, the coefficient on the unemployment rate is positive and rather uniform across education groups. However, the unemployment rate has very little variation between and within countries, and the economic significance of the coefficient is rather limited. The positive association between the share of migrants from the same province of origin and the likelihood of residing in a particular country is merely mechanical and serves here just as a control variable.

A crucial assumption of most discrete-choice models is the independence of irrelevant alternatives. The violation of this assumption cannot be excluded here, neither intuitively nor by a Hausmann test. One possible way to circumvent this problem would be to run a multinomial Probit. However, this is computationally infeasible with so many options and observations as in our case. Hence, we adopt a different approach: We subdivide the sample into close and far away locations.

[14] Language relatedness is measured as the genetic distance between languages, on a scale from 0 to 100, retrieved from the project eLinguistics.

For both sub-samples, the results confirm our main finding; namely, a positive and significant effect of disposable household income on the migration choice.

6.3 Impact of redistribution

As the findings presented above clearly indicate, redistributive policies should be evaluated with an eye to their impact on migration patterns. Here, we attempt to estimate how emigration flows from Italy would be affected by changes in governmental income redistribution in Italy. We perform a back of the envelope calculation using our estimates of Section 6.2 to evaluate the reaction of individuals with different skill levels to a change in their returns from migration induced by a redistributive policy in Italy, leaving unaltered the circumstances prevailing in the potential destination countries (i.e. we neglect general-equilibrium effects).

Our policy exercise also neglects the impact of Italian redistributive policy on the decisions of foreigners who may migrate to Italy. The bulk of international migration to Italy originates from Eastern-Europe, Africa, and Asia (Istat, 2019), also including a considerable number of illegal immigrants estimated to be between 7 and 12 percent of foreign residents (OECD, 2018). Of course, illegal migrants are excluded from social transfers. An additional amount of redistribution in Italy might increase the incentive to migrate to Italy for those individuals who expect to acquire a legal migrant status later on. This may, however, be offset by higher remittances that make their family members remain in the source country. Given the lack of data, we simply assume that such migration flows do not respond to changes of distributive policies in Italy.

Consider a small, budget neutral, increase of progressivity in Italy, approximated by a linear redistributive scheme on top of the currently existing tax-transfer system. This scheme consists of a yearly demogrant $G > 0$ received by all adult Italian citizens living in Italy that is financed by a proportional tax on those citizens' gross incomes. Assuming that the general-equilibrium effects of this measure are of the second order, we ensure budget neutrality of such an operation with respect to the ex-ante resident population. This yields an increase in household disposable income for a resident that is given by

$$\Delta = nG(1 - \frac{Y^{gross}}{n\overline{Y}}), \quad (9)$$

where Y^{gross} is the household gross income and $\overline{Y}$ the average per-adult household gross income of the resident population aged 35-55; n is 1 if the household has a single adult and 2 for couples. As shown by equation (9), households with below-average income gain from this policy, households with above-average income lose, and the size of the gain strictly decreases with household gross income. The degree of progressivity of this policy is fully captured by the demogrant: the larger is G, the more progressive is the policy.

As we did for net incomes, we also predict the gross household incomes in Italy, and their average for the resident population, using LIS data. We run a Mincer regressions including sex, age, quadratic age, and education on the resident population aged 35-55 and use the coefficients of this regressions to predict the gross incomes of Stayer, as well as the counterfactual incomes in Italy for the migrants in our sample.

Using equation (8) from Section 6.2 we can estimate variations in migrations flows induced by higher progressivity in Italy. For illustration purposes, we compute the predicted effects of a policy that sets $G = 1,000$ USD PPP while keeping constant the net incomes in the other countries.[15] We employ an alternative-specific conditional logit – used before and described in Section 6.2 – replacing Y^{net} with $Y^{net} + \Delta$ in the case of staying in Italy. Hereafter, we compare how the predicted probabilities to migrate or to stay in Italy vary when adopting the estimated parameters for each education group. Table 9 shows the results of this exercise. We find that the policy would induce 0.04 % of the total population of less educated individuals to remain in Italy rather than leave the country, and approximately 0.12 % of the highly educated to leave Italy. We also predict that about 0.006 % of the Italian population with an intermediate level of education would prefer to stay in Italy if these redistributive measures were enacted.

[15]The Italian GDP measured in international Dollars PPP in 2017 was about 2,311 Billions (Source: World Economic Outlook 2017, International Monetary Fund, April 2018). The Italian adult population is about 52 Million people. The policy we investigate would thus have a fiscal impact of about 2.3 percentage points of Italian GDP.

Table 9: Policy Experiment - Predicted Change in Migration Flows for $G = 1000$

	Level of Education								
	Low			Middle			High		
	Share (in %)	$Pr(Y^{net})$	$Pr(Y^{net}+\Delta)$	Share (in %)	$Pr(Y^{net})$	$Pr(Y^{net}+\Delta)$	Share (in %)	$Pr(Y^{net})$	$Pr(Y^{net}+\Delta)$
AUS	0.02	0.03	0.03	0.03	0.02	0.02	0.06	0.03	0.03
BRA	0.01	0.02	0.02	0.03	0.01	0.01	0.05	0.04	0.05
CAN	0.02	0.03	0.03	0.03	0.02	0.02	0.05	0.02	0.02
CH	0.24	0.15	0.14	0.22	0.18	0.18	0.46	0.71	0.75
FRA	0.02	0.07	0.07	0.06	0.05	0.05	0.26	0.12	0.13
GBR	0.07	0.20	0.19	0.24	0.20	0.20	0.66	0.36	0.38
GER	0.47	0.35	0.34	0.18	0.28	0.28	0.33	0.41	0.43
ITA	99.10	99.07	99.11	99.04	99.12	99.13	97.58	97.70	97.58
NLD	0.00	0.02	0.02	0.01	0.01	0.01	0.07	0.02	0.02
USA	0.06	0.06	0.06	0.16	0.09	0.09	0.48	0.59	0.61
Total population (Mover and Stayer)	8,076,831			5,860,798			2,848,098		
Change in outflows		- 0.040 %			- 0.006 %			0.124 %	
In-sample population change		- 3204			- 338			3542	
Extrapolation	$q^* = 1.41$	- 4518			- 476			4994	
	$q^u = 1.52$	- 4870			- 513			5384	
	$q^l = 1.28$	- 4101			- 432			4534	

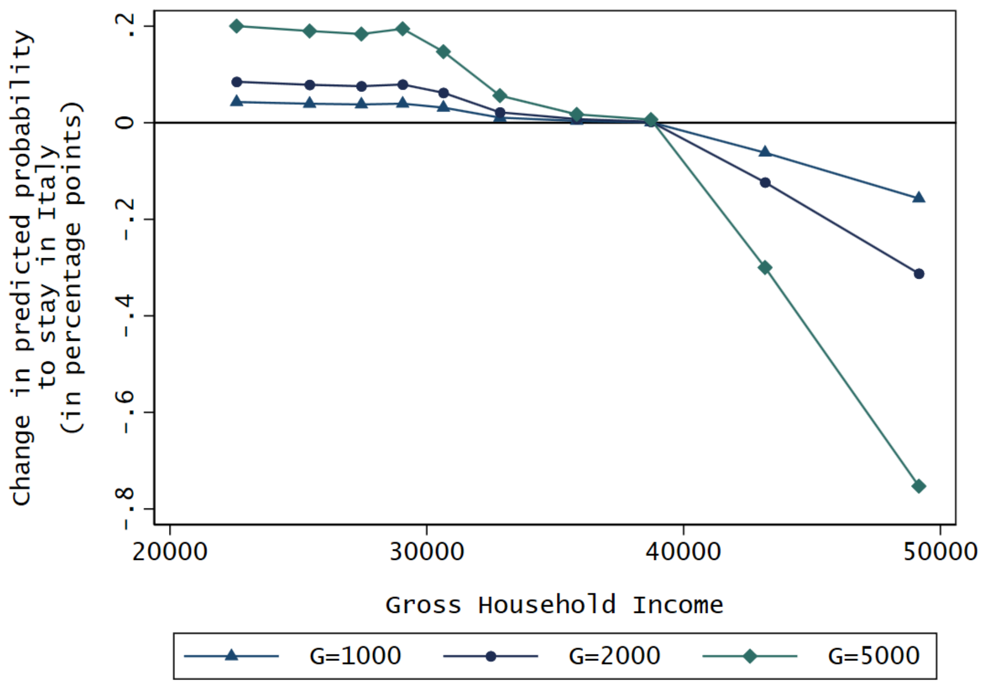
Notes: Upper part of the Table shows the weighted shares of Italian citizens residing in the distinct countries by their level of education compared to the predicted probabilities of the alternative specific conditional logit models estimated on the predicted net household income before and after adding Δ. Lower part of the Table shows: The weighted total population of Italian citizens for each education group, including stayer and mover in each of the nine possible destination countries of this exercise. The estimated percentage change in outflows from Italy to the other countries. The absolute population change of flows from Italy to the countries in the sample, and an extrapolation of the change in worldwide flows applying different extrapolation factors. Source: AIRE, SHIW, and LIS, own estimates.

In absolute terms, the relocation pattern caused by this policy across all education groups is predicted to concern some 7,000 individuals, and to leave the total number of residential population in Italy virtually unaffected. However, this estimation fails to capture relocation incentives that concern destination countries not included in our sample. To grasp how this translates in absolute terms on the change in the total number of potential Italian movers worldwide, we simply apply an extrapolation factor. We define this factor as $q = \frac{N^{tot}}{N^{sample}}$, where N^{tot} is the total number of Italians born in Italy that live abroad, including both the countries that we have at our disposal and the rest of the world; N^{sample} is the number of observations in our sample used for this exercise. Since we only have the information about the total number of Italians registered as living abroad (4,636,647), and do not know how many of these were born in Italy, we approximate this number adopting the same share of Italians born in Italy that we observe in our data. The average share of Italian migrants born in Italy over all Italians living abroad is 31.39 % in the AIRE data at our disposal, ranging from 8.16 % in Brazil to 53.36 % in the US. Using the average value yields an extrapolation factor of $q^* = 1.41$. We keep the other two shares to estimate a lower and an upper bound; $q^l = 1.28$ and $q^u = 1.52$, respectively. Based on this extrapolation procedure, the simulated redistributive policy prompts around 4,500 individuals with low educational attainment to stay in Italy rather than move to a foreign country. The same policy causes around 5,000 highly educated individuals to leave their country of origin.[16]

In the last part of this exercise, we measure the effects of the considered reform at different quantiles of the income distribution. Furthermore, we vary the level of the demogrant G. Figure 15 shows the results of this sensitivity analysis. As is evident, the pattern does not change and the effects become stronger with rising G. For instance, the probability of top income earners in the highest decile to leave Italy is about four times higher when the demogrant is set to an amount of 5,000 USD PPP.

[16]When the relative quality difference of educational systems between countries is taking into account, the number of low educated staying in the source country is 4,023 while 4,211 high educated leave. All results can be found in the Supplemental Material.

Figure 15: Policy Experiment - Predicted Change in Outflows and Net incomes for $G > 0$ by Level of Household Income



Notes: Graph shows the predicted changes in the probability to stay in Italy after policies that change net household income by Δ for different amounts of G. Dots show corresponding values of the deciles of the distribution of gross household income. Source: AIRE, SHIW, and LIS, own estimates.

Finally, we investigate how the top 1 percent of the distribution would react to the reform. Our results show that in the top percentile the probability to stay in Italy decreases by 0.20, 0.40, and 0.92 percentage points for G equal to 1,000, 2,000, and 5,000 USD, respectively. Applying the out-of-sample extrapolation explained above, this translates into 422 top-one-percent income earners leaving Italy as a consequence of the reform with $G = 1000$ (for $G = 2000$ and $G = 5000$ the numbers are 844 and 1942 people, respectively). In our exercise, these people contribute to around 0.009 percent of the entire amount redistributed by the government through this reform. Since the survey data we use to impute incomes fail to cover the super-rich, these findings do not contradict the literature that reports strong migration responses to taxation of the super-rich.

7 Conclusions

This paper has studied the impact of governmental income redistribution at the country level on the skill composition of international migration flows. Our key contribution is to employ, for the first time, a large administrative dataset of the Italian government that includes the bulk of the population of Italian citizens living abroad. In addition to its advantages in terms of reliability and coverage, this dataset offers a precious opportunity to test the predictions of the Roy model because Italy is a country with an intermediate degree of income redistribution, with ample outflows of workers both to more progressive countries and to less progressive ones. We can thus simultaneously assess the welfare-magnet effects exerted upon the low-skilled and the rich-repulsion effects exerted upon the high-skilled.

Our results confirm the predictions of the underlying theory: a lower degree of income redistribution is significantly associated with a positive skill selection of Italian immigrants. On the contrary, countries with more progressive tax and transfer systems largely attract immigrants from the lower end of the skill distribution. The statistical significance of these patterns is confirmed by a multitude of distinct exercises and test procedures.

The relevance of taxes and transfers in shaping migration incentives is often stressed in policy debates, usually in order to argue in favor of reducing progressivity, and sometimes in order to call for internationally coordinated taxes. In order to better inform this debate, we have run simple policy experiments in our setting, quantifying the impact of additional income redistribution in Italy on the migration choices of Italian citizens. Our results indicate that even large increases in the degree of redistribution have small effects on the skill composition of the resident population in Italy.

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Supplemental Material:

http://gneid.weebly.com/uploads/1/1/2/7/112751241/appendix_v3.pdf