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ABSTRACT

Education-occupation mismatch of migrants in the Italian labour market: the effect of social networks

Whilst migration has become a structural feature of most European countries, the integration of foreigners in the labour market continues to raise concerns. Evidence across countries shows that migrants are more often over-educated than natives. Over the last years, scholarship has intended to capture the effect of informal networks on migrants' over-education. Interestingly, no study has looked into the Italian case, yet a country for which the effect of networks on education-occupation mismatch is well documented. This article has two objectives: it assesses the extent to which over-education affects migrants and it evaluates the role informal networks play in producing it. We find that foreigners are more over-educated than natives but that the role of networks is consistent across the two groups. Empirical evidence is drawn from the application of quantitative and counter-factual methods to PLUS 2018 – Participation, Labour, Unemployment Survey.

KEYWORDS: network, over-education, migrants, labour market

JEL CODES: F22, J61, Z13

1. Introduction

Whilst migration has become a structural feature of most European countries, the integration of foreigners in the labour market continues to raise concerns. In an ageing Europe, migration presents indubitable positive economic effects. By feeding the workforce, it alleviates the old-age dependency ratio (the number of workers compared to that of pensioners) and the risks looming over the European population's ability to sustain its economy (European Commission 2011). But migrants' contribution to their receiving country's economy is by no means immediate. Coming from different cultural, linguistic and institutional backgrounds, migrants need to adapt to a reasonable extent to the pre-existing structures of their receiving societies. Consequently, there may exist a mismatch between foreigners' education and their occupation; a mismatch that, ideally, would be temporary and vanish swiftly.

Scholarship tends to converge on the existence of a complementarity between domestic and foreign labour forces (Dustmann *et al.* 2005; Venturini and Villosio 2002; Esposito *et al.* 2020). Yet, there appears to be a significant difference between foreigners' and nationals' education-occupation mismatch (Piracha and Vadean 2013; McGowan and Andrews 2015). The specialised literature has put forth a series of explanations such as imperfect information (Dolado *et al.* 2009), imperfect transferability of human capital across borders (Chiswick and Miller 2009) or even work experience – or mismatch – in the country of origin (Piracha *et al*. 2012). Over the years though, the attention has been moving towards the role of job-search channels in generating mismatch, with particular emphasis on informal ones (Chort 2016; Kalfa and Piracha 2018; Alaverdyan and Zaharieva 2019). Namely, resorting to family and friends to look for and find a job would be associated (or not) with over-qualification. Studies have thus far investigated specific migrant communities or specific countries. None of them has investigated the Italian case, yet a country where the relationship between informal channels and mismatch is well-documented (Pistaferri 1999; Mosca and Pastore 2008; Meliciani and Radicchia 2016). Following our estimates, as of 2018, over-qualification in Italy regards approximatively 20.2% of Italian nationals currently in employment and 21.1% of foreign nationals currently in employment in the country. Such a difference appears greater when we account for foreigners' migration background: whilst 16.7% of those who prevalently grew up in Italy are over-qualified, they are 22.5% amongst foreigners who grew up abroad and migrated to Italy subsequently.

This article aims at shedding light on the phenomenon. Relying on PLUS data – Participation, Labour, Unemployment Survey, a survey conducted by the Italian National Institute for Public Policies Analysis (Inapp) – we seek to assess the likelihood of mismatch for both populations and the role informal channels play in generating it. Our empirical strategy is twofold. Firstly, we compute the probability of mismatch occurring with regard to over-education. Secondly, we apply counterfactual methods to reinforce our causal claims. We thus implement a propensity score matching (PSM) model to put natives and foreigners on a par. Then we rely on inverse-probability treatment weighting methods (IPW) to compare the probability of over-education for natives, foreigners who prevalently grew up in Italy and foreigners who migrated later on in their life.

We find evidence of a difference in over-education between foreigners and natives; a difference that is clearer when we distinguish between the foreigners who grew up in Italy and those who migrated later in their life. The former are undistinguishable from natives whilst the latter tend to be significantly more over-educated. As for the effect of networks, it appears to be consistent across our three groups: irrespective of one belonging to one group or another, the use of networks consistently decreases over-education. Our article is divided as follows. The second section selectively reviews the specialised literature on migrants' over-education and on education-occupation mismatch. We also refine our contribution to said literature. The third section outlines our empirical strategy and our data. The reader most interested in the technicalities of our method may find more information in the appendix. The fourth section presents our empirical results while the fifth discusses them. We conclude in a sixth section.

2. Literature review

2.1 The over-qualification of migrants

The adjustment of migrants into their receiving country's labour market has been extensively studied, with origins dating as far back as early Chicago School, at the instigation of Park (Park *et al.* 1921). Using natives as the gold standard, scholarship has intended to assess the extent to which immigrants becomes more similar to natives in terms of earnings and occupation. Put differently, those studies have aimed to assess whether migrants become economically 'assimilated' (Constant and Zimmermann 2013). In this respect, the pioneering work of Chiswick (1978) has considerably influenced current scholarship. He posited that, due to imperfect transferability of human capital across borders, migrants would initially have lower earnings than natives. With the passage of time, migrants would gain information and adjust to the functioning of the labour market; they would eventually catch up with natives' earnings.

More recently, the attention has turned to another, yet related, important feature of labour market performance: the match between education level and occupation; more specifically, occupational mismatch, and particularly over-education. Whilst mismatch is an issue that generally affects labour markets in market economies (McGowan and Andrews 2015; Leuven and Oosterbeek 2011), evidence tends to converge towards the existence of a significant difference between natives and foreigners: migrants are consistently more over-educated for the positions they occupy than natives (Piracha and Vadean 2013; McGowan and Andrews 2015). According to European Social Survey data covering the year 2000-2009, 13% of the native respondents across 22 European countries were over-educated for their jobs whilst the figure rose to 22% for foreigners (Aleksynska and Tritah 2013). Such figures appear to be similar in other OECD countries, as it is, for instance, in Australia, with respectively 17% of natives and 22% of foreigners being over-qualified over the years 2001-2011 (Kalfa and Piracha 2018).

Different explanations were put to the test. Drawing upon Chiswick's (1978) work on earnings, some studies have posited the role of information adjustment. Accordingly, migrants would need to get acquainted with the functioning of the labour market in order to transfer their human capital to the full (Chiswick and Miller 2009). Differently, Mattoo *et al.* (2008) have pointed at the role of the quality of the human capital that is being transferred. They notably argue that a large part of over-education is due to the attributes of the country of origin. Instead, Piracha *et al.* (2012) have posited the effect of mismatch in the country of origin on mismatch in the receiving country. Yet other explanations have put forth the role played by the characteristics of the receiving society. Cultural proximity (especially regarding language[1]) and natives' attitudes towards foreigners (namely discrimination[2]) likely affect labour market integration. Over the years though, the attention has moved towards the role of informal job-search channels in generating over-education (Chort 2016; Kalfa and Piracha 2018; Alaverdyan and Zaharieva 2019). Inspired by the vast literature on the effect of referral hiring on mismatch (Montgomery 1991; Pistaferri 1999; Meliciani and Radicchia 2016), the few studies available thus far have produced conclusions in shades. Kalfa and Piracha (2018) have demonstrated that social capital exacerbates migrants' education-occupation mismatch in the Australian labour market. Alaverdyan and Zaharieva (2019) present concurring results for the German case. Conversely, Chort (2016) studies the effect of the use of informal channels within the Senegalese community across four countries – France, Italy, Mauritania and Ivory Coast – and concludes to the positive effect of networks on education-occupation match. This article contributes to this growing strand in literature for several reasons. Firstly, we investigate the Italian case, a country for which the relationship between informal channels and mismatch is well-documented (Pistaferri 1999; Mosca and Pastore 2008; Meliciani and Radicchia 2016).

Secondly, we rely on respondents' declared use of informal networks. Whereas other studies have relied on composite and indirect indicators of network use (Kalfa and Piracha 2017), we consider the intensity of networks use by the respondents, which we compare to eleven other channels – amongst which job centres, professional networks, and temporary work agency – as well as the occurrences in which networks have actually led to employment.

Finally, another significant contribution lies with the decomposition of the foreign population into different groups; namely separating migrants with a migration background (i.d. who prevalently grew up in Italy) from people who migrated from their home country to Italy subsequently. This is an important distinction as foreigners who grew up and went to school in Italy are more likely acquainted to Italy's economy and labour market. Conversely, those who migrated to Italy have had to learn some Italian and gain information on the labour market's functioning.

2.2 Defining mismatch

There exist three main ways to measure education-occupation mismatch (ILO 2018): the normative approach, workers' self-assessment and the statistical approach. All three approaches carry different information and does not necessarily overlap with one another (ILO 2018). In the first approach, mismatch is measured using a classification elaborated ex-ante, which specifies the level of educational attainment required for each occupation. Whilst this method is regarded as perhaps the most accurate (Green *et al.* 2007), it requires extensive data and is therefore discarded for the purpose of this article.

[1] Language proficiency was proven to significantly affect migrants' labour market outcomes (Dustmann and Van Soest 2002). Consequently, migrants coming from countries which speak the same language as that of the receiving society are likely to perform better.

[2] In this regard, see Neumark 2013.

Differently, self-assessment provides the workers' perception of their own mismatch. Whilst an interesting dimension, it does not necessarily fit every research purposes[3] inasmuch as it can be affected by classification error as the researcher does not know how the respondent elaborated her/his judgment (Chevallier 2003). In a similar fashion, this method is presumably little suitable if it comes to comparing different groups with intrinsic differences as they likely display very different characteristics underlying their perception of mismatch[4].
Finally, the statistical approach is based on the distribution of workers' education levels within occupational groups. Whilst not as precise as the normative approach, its relying on statistical distributions and the distance of a given worker from the latter provide a relatively objective measure of education-occupation mismatch, all the more so if we intend to compare two groups such as migrants to natives. More precisely, since it is based on the distance of an individual from the mean, or the mode education level (depending on the method chosen), it allows for measuring whether this distance is statistically more often observed for natives or for foreigners, all other things being equal. Of course, it is not a measurement exempt of drawbacks as it is sensitive to the aggregation level of the occupations' classification as well as cohort effects (since it is based on observed distribution of education for a given occupation; see Chevallier 2003). Notwithstanding, and given the cross-section nature of our analysis, we consider that the third approach is here the best alternative to the normative method. Not as data-demanding as the latter, it is more suitable for our purposes than the subjective perception of mismatch, for that it allows to compare different groups without considering underlying determinants of perceptions, as it would be with the self-assessment method.

3. Mismatch in Italy: data, descriptive statistics and empirical strategy

3.1 Empirical strategy

Our analysis relies on data collected by the Italian National Institute Public Policies Analysis[5] through PLUS (Participation, Labour and Unemployment Survey), a survey on the Italian population in working age conducted every second year. The sample we use is that of PLUS 2018[6]. It counts a total of 45,000 observations, about 2%, of which regarding foreigners. Note, though, that our research interest lies with the respondents available for work. We therefore exclude pensioners and students from our empirical analysis. This results in a sample of 31,600 observations, of which 2.4% are foreigners. The relatively low proportion of foreigners in the sample is in contrast with the percentage of foreigners

[3] One of the issues associated to self-assessed mismatch lies with the possible confusion between vertical (education level) and horizontal (field of study) mismatch. For more on such a distinction, see Chort (2016) and Robst (2007).
[4] As Borjas (1988) argued, migrants are not sorted at random but self-selected; they rationally decide whether and where to migrate by comparing various opportunities. If this theory has been moderated over the years, notably by the New Economics of Migration school (Zanfrini 2016), self-selection remains an important determinant of the composition of migration flows.
[5] Inapp, see https://inapp.org/.
[6] Further details about PLUS 2018 are in Gallo and Scicchitano (2019) De Minicis *et al.* (2019) and Esposito and Scicchitano (2020a; 2020b).

in Italy, estimated at around 8.5% in 2018[7]. Resultantly, we opt for a twofold approach which, on the one hand, seeks to use all the information available and, on the other hand, selects the observations considered to put foreigners and natives on an equal footing. The former is implemented via probit regressions on the whole sample whilst the latter draws from counterfactual methods to correct the low percentage of foreigners in our sample. Both approach are explained in greater detail in the methodology section below.

3.2 Data and variables

In accordance with the definition of mismatch introduced above, a worker is regarded as under- or over-educated if their education level is respectively lesser or greater than the mean or modal educational level (ILO 2018). Whilst the original version of the statistical approach rested on the mean of the education distribution (Verdugo and Verdugo 1989), we here follow Kiker *et al.*'s measurement (1997) which compares the actual level of education of an individual worker to the modal level of education of all workers in their occupational group. This choice is notably due to the nature of the data at hand. Education levels and occupation groups are defined in accordance with international standard classifications; namely ISCED and ISCO one digit. Whereas ISCED one digit provides a fair idea of people's education levels, ISCO one digit is an aggregation levels that does not allow a fine-grained analysis. It is however good enough to study differentiated distributions for two to three groups. For the purpose of this article, we shall focus on over-qualification. Mismatch is calculated on the basis of the modal education level of those in employment for a given occupation category. Note that we consider mismatch with regard to current employment but also former employment in case the respondent is unemployed and looking for a job. The mode education for the employed is thus applied to the unemployed. Table 1 below summarises the data as to education, occupation and over-qualification for the two groups under scrutiny.

The use of informal networks is captured by two different questions in the questionnaire. Firstly, "among the following job-search methods, can you tell me which one you have used and to what extent?" Respondents were listed 12 items and had the possibility to indicate the intensity of their use on a scale from 0 to 10. The item that interests us the most is the one reading: "friends, relatives and acquaintances". In order to take account of all 12 items, we ranked them according to their intensity of use in order to obtain a more precise idea of the way respondents look for jobs. We then multiplied the inverse rank by the declared intensity (on a 0-10 scale) to obtain a more precise measurement of their use, and then divided the result by 10 so as to have a more interpretable scale, ranging from 0 (little use compared to other job-hunt means, low intensity) to 12 (most used channel and one used intensely). Secondly, we considered the channel through which respondents obtained their current job as another indicator of the use of networks. Note that the two measurements are highly correlated (with a Pearson's polychoric coefficient of 0.71). The limitation of this variable lies with the fact that we do not have information regarding the composition of networks, whether they are principally made up of co-ethnics or if they are mixed networks (see Neumark 2013, for more on network hiring).

[7] ISMU Foundation estimates the foreign population legally residing in Italy in early 2018 at around 9.2% of the total population in the country (Blangiardo 2019, 21).

Table 1. Education, Occupation and Over-qualification in Italy for Italians and foreigners available for work (%)

	Nationals	Foreigners	All
Education levels			
Elementary	1	2.1	1
Lower middle	16	17.8	16
High school	48.6	49.6	48.7
Bachelor	30.5	27.1	30.4
Post bachelor	3.9	3.4	3.8
Total	100	100	100
Occupation classification			
Chief executives, senior officials and legislators	4.5	3.5	4.5
Intellectual and science professionals	24.5	14.9	24.3
Technicians and associated professionals	16.7	13	16.7
Clerical support workers	20.5	10	20.3
Service and sales qualified workers	13.9	34.2	14.4
Skilled and agricultural workers, Craft and related trades workers	9.8	7.9	9.7
Plant and machine operators and assemblers	3.8	3.5	3.7
Elementary occupations	6.1	12.8	6.2
Armed forces occupations	0.3	0.2	0.3
Total	100	100	100
Over-education			
Chief executives, senior officials and legislators	10.5	6	10.4
Intellectual and science professionals	15.1	8.2	14.9
Technicians and associated professionals	32.6	26.1	32.4
Clerical support workers	28.9	17.9	28.6
Service and sales qualified workers	8.8	29.1	9.4
Skilled and agricultural workers, Craft and related trades workers	1.8	2.2	1.9
Plant and machine operators and assemblers	0.7	0.8	0.7
Elementary occupations	1.2	9.7	1.4
Armed forces occupations	0.4	0	0.4
Total	100	100	100

Source: Inapp PLUS 2018
Note: pensioners and students were excluded from the sample.

As for the foreign population, we distributed people who were not born with the Italian citizenship[8] into two categories: those who have prevalently grown up in Italy (from 0 to 18 years old) – hereinafter, with a migration background – and those who prevalently grew up abroad (hereinafter migrants). For the latter group, we also consider the geographic area they come from (Mattoo *et al.* 2008) and the number of years spent in Italy, as a proxy for information adjustment (Chiswick and Miller 2009) and language proficiency (Dustmann and Van Soest 2002). Such distinction appears of

[8] We therefore excluded from the analysis the Italian nationals born and brought up abroad who returned to Italy.

the utmost importance, notably if we consider the distribution of mismatch across categories (see table 2). Note that this distinction is also likely to affect the composition of informal networks, with those of migrants being made up of co-ethnics, whilst those of foreigners who grew up in Italy being more mixed. The data at hand does not allow us to test this hypothesis.

Table 2. Distribution of over-qualification according to background and employment situation (%)

	Over-qualification in employment	**Over-qualification total workforce available**
Nationals	20.3	18.1
Foreigners	21.1	21.5
Grew up in IT	*16.7*	*16.9*
Migrated to IT	*22.5*	*23*

Source: Inapp PLUS 2018
Note: total workforce includes people in employment, unemployment and inactive in search of employment.

We control for a series of factors that may affect mismatch. The area of residence – North, Centre or South – is of particular importance for a country like Italy, characterised by different territorial patterns of labour market dynamics and, consequently, different patterns of migrant integration (Ambrosini 2013; Zanfrini 2014). Similarly, we also control for the type of agglomeration in which the respondents resides insofar as rural or urban environments likely offer different work prospects. We also control for demographics such as gender, whether the respondents have children, work status (note that students and pensioners were excluded from the analysis), father's education level and sector of activity (whether public or private). Finally, a last control aims at capturing the period of time in which mismatch occurred. It thus consists in the year in which occupied respondents took up their current job and the year in which unemployed respondents had their last job.

3.3 Methodology

Our methodological approach is twofold. Firstly, we run a series of probit regressions to compute the probability of over-qualification for natives and migrants (who have either migrated or grown up in Italy). In this manner, we use all the information available. The downside of it is the unbalanced sample, featuring about 2.4% of foreigners. Secondly, we draw from counterfactual evaluation methods (Rubin 1974) to correct our unbalanced sample. On the one hand, we implement a propensity score matching model (PSM; Rosenbaum and Rubin 1983) in order to put natives and foreigners on a par. In this case, we consider being foreigner as the 'treatment', so to speak, and create a control group of natives with *very* similar characteristics (considering the large pool of controls). On the other hand, we further break down the effect of being foreign into two categories: those who migrated and those with a migration background. In order to estimate the effect of belonging to these two groups compared to the group of natives, we rely on the inverse-probability of treatment weighting method (IPW; Curtis *et al.* 2007; Cattaneo 2010). This section briefly outlines the methodology used. More detail as well as robustness tests are available in the appendix.

Probit regressions. With regard to probit regressions, we report the results of 10 models. The first four are the simplest specifications, displaying the raw effect of migration status and informal networks onto education-occupation mismatch. Models 5 through 8 are comprising of our covariates and controls; model 6 and 8 are also tested (though not reported for ease of reading) with an interaction term between migratory background and use of networks in order to test the joint effect of the two variables. Models 9 and 10 are partial regressions on the subsample constituted by foreigners who grew up abroad. These allow testing other hypotheses, such as the effect of migrants' length of stay or their area of origin, on mismatch.

Propensity Score Matching. As for propensity score matching, the scores are computed on the probability (logistic model) of a respondent to be a foreigner considering gender, the presence of children, whether the respondent works in the public or private sector, the area of residence, age, city size, education, father's education and work status. Given the composition of the database (about 2.4% of foreigners), the pool from which to draw possible matches is quite large and allows for precise matching, thus reducing the bias introduced by unequal means for each of the variables in the sample. The propensity score is defined as the conditional probability of receiving a treatment, given pre-treatment characteristics (Rosenbaum and Rubin 1983), so that:

$$p(x) = \Pr\{D = 1 \mid X\} = E\{D \mid X\} \tag{1}$$

where $D = \{0,1\}$ is the indicator of exposure to treatment and X is the vector of pre-treatment characteristics. For our purposes, treatment refers to being foreign. Following equation (1), observations with similar propensity scores are also similarly distributed with regard to observables and unobservables, regardless of their treatment status (that is, being a foreigner or not). Put differently, exposure to treatment is random and foreigners and natives are, on average, very similar. This assumption holds only if the balancing property, such that $D \perp X \mid p(x)$, holds too. Our tests suggest that it does (see appendix).

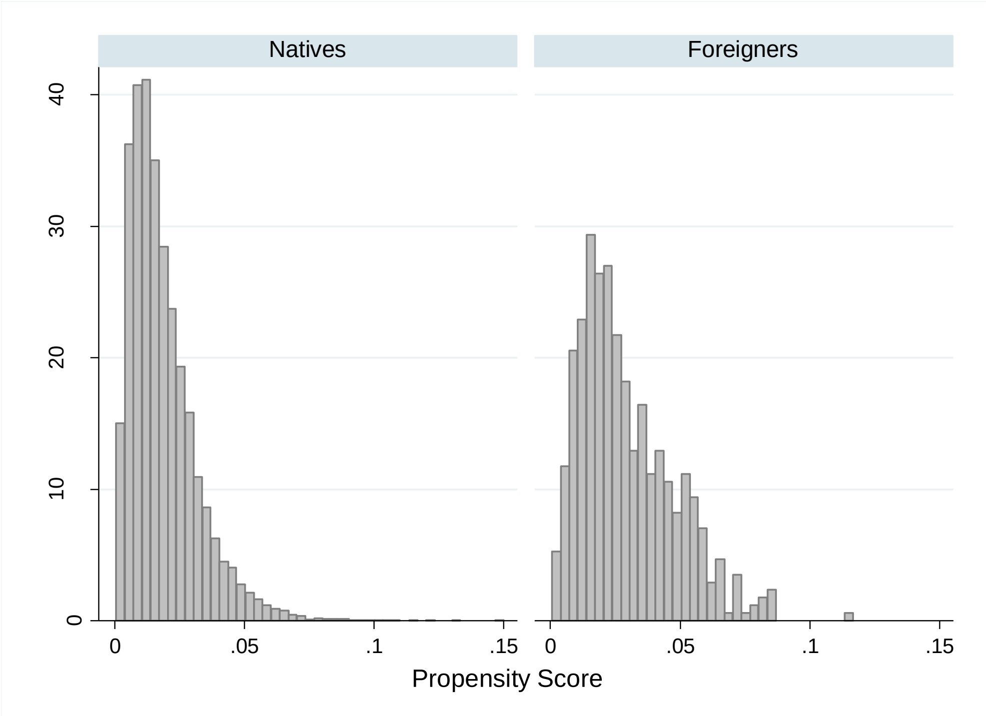
Once we ensured the balancing property is satisfied, we computed different estimations of the average treatment effect on the treated (ATT) to assess how much of over-education is due to the treatment; i.e. being a foreigner. The ATT is estimated as follows:

$$\begin{aligned} \tau &\equiv E\{Y_{Mi} - Y_{Fi} \mid D_i = M\} = E\{E\{Y_{Mi} - Y_{Fi} \mid D_i = M, p(X_i)\}\} = \\ &= E\{E\{Y_{Mi} \mid D_i = M, p(X_i)\} - E\{Y_{Fi} \mid D_i = F, p(X_i)\} \mid D_i = F\} \end{aligned} \tag{2}$$

where the outer expectation is over the distribution of $(p(X_i) \mid D_i = 1)$ and Y_{Mi} and Y_{Fi} are the potential outcomes for the two groups (foreigners and natives), representing the two counterfactual situations of treatment and no treatment. As p(X) is a continuous variable, the probability of observing two units with exactly the same value of the propensity score is very small. We therefore resort to matching methods in order to associate observations in the treatment group with observations in the control group. These methods are: nearest neighbor, Kernel matching (with bootstrapped standard error; 20 repetitions) and radius matching (with radius size = 0.01). The effect of network is subsequently estimated through probit regressions with the observations weighted by their propensity scores.

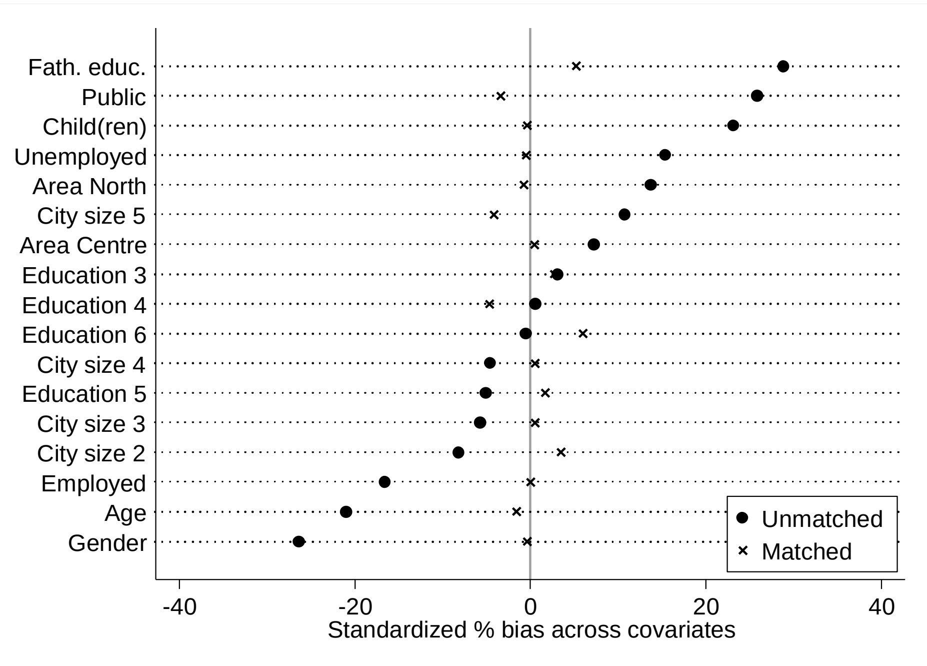
The calculation of propensity scores yields sound results that may be assessed through comparison between foreigners' and natives' scores. Figure 1 shows a rather homogeneous distribution of the propensity scores between the two groups, thus guaranteeing the accuracy of matching methods as comparison can be restricted to common support. Our tests suggest that the balancing property is met.

Figure 1. Density histograms of the propensity scores for foreigners and natives



Source: Inapp PLUS 2018

Figure 2. Propensity scores' bias correction after matching (%)



Source: Inapp PLUS 2018

Figure 2 shows a significant bias correction from the unmatched to the matched sample, thus suggesting that the propensity score does a good job at balancing observations across variables by significantly reducing the bias present in the sample.

Inverse Probability Weighting. The inverse-probability weighting approach corrects selection bias through attributing each observation a weight inversely proportional to its probability of selection (Curtis *et al.* 2007; Cattaneo 2010). Thus, we calculate observations' weights according to their propensity to fall in any of our three categories – native, migrant or migration background. For the propensity model, we use the same covariates as those used to calculate propensity scores with the logistic model above. We estimate a multinomial logistic model to calculate our observations' weights according to their propensity to fall in any of our three categories. The propensity to fall in any of the three groups is calculated considering natives as the reference group (or control group) such that:

$$\Pr(t = 1 | X) = \phi(X) \tag{3}$$

where t is the treatment variable assuming the values 0 for natives, 1 for foreigners who grew up abroad and 2 for foreigners who grew up in Italy. Like for PSM, X is a vector of observables used to calculate the probability of falling in any of our three groups. Following Feng *et al.* (2011) and Lopez and Gutman (2017), the effect on the treated is calculated as follows:

$$ATT_{t1,t2} = E[Y_i(t_1) - Y_i(t_2) \mid T_i = t_1] \tag{4}$$

where $ATT_{t1,t2}$ is the average treatment effect on the treated for those receiving t1, Y_i is the outcome, t the treatment and T_i the treatment assignment. The estimand assesses the effect of the treatments through pairwise comparison. Pairwise ATT is transitive, so that:

$$ATT_{t1|t1,t3} - ATT_{t1|t1,t2} = ATT_{t1|t2,t3} \tag{5}$$

Accordingly, the average effect on the treated if treatment = 1 is equal to equation (4) where:

$$E[Y_i(t_1)] = \left(\sum_{i=1}^{n} \frac{I(T_i = t_1)Y_i}{r(t_1, X_i)}\right)\left(\sum_{i=i}^{n} \frac{I(T_i = t_1)}{r(t_1, X_i)}\right)^{-1}$$

and (6)

$$E[Y_i(t_2)|T_i = t_1] = \left(\sum_{i=1}^{n} \frac{I(T_i = t_2)Y_i}{r(t_2, X_i)}\right)\left(\sum_{i=i}^{n} \frac{I(T_i = t_2)}{r(t_2, X_i)}\right)^{-1}$$

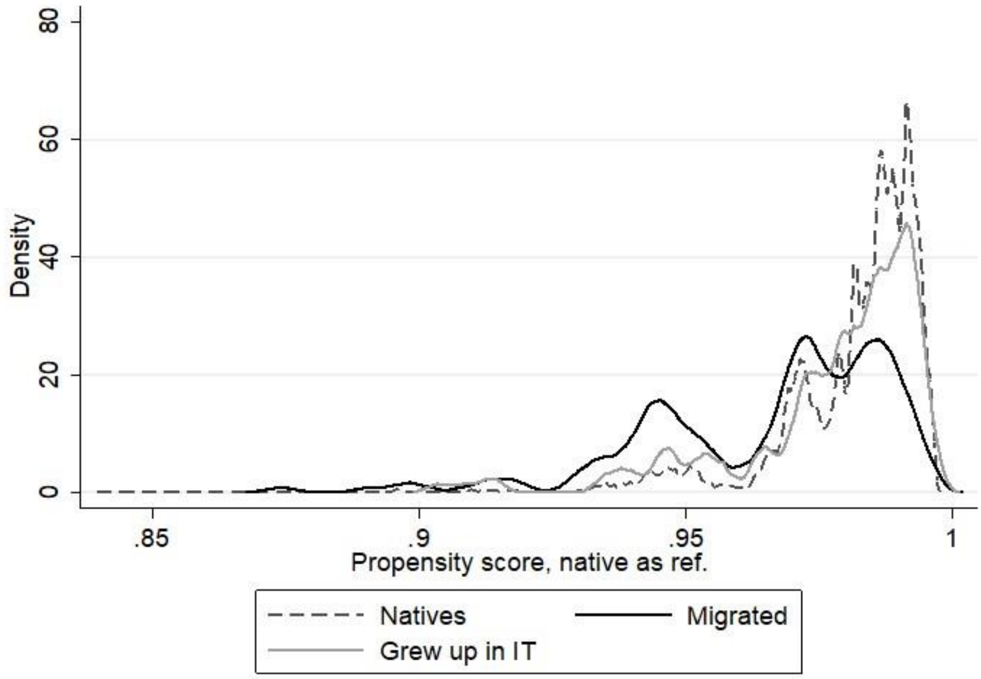
where $I(T_i = t_i)$ is the indicator for an individual receiving treatment t_i and $r(t_i,X_i)$ is the propensity score such that $r(t_i,X_i) = \Pr(t_i \mid X)$. The model implemented displays satisfying overlap between the three statuses possible (see appendix).

We finally provide estimates of the effect of informal networks onto over-education with the use of probit regression models, which account for the inverse-probability weights calculated prior.

The conditions for the validity of IPW are chiefly two: the size of the weights; and their overlap. Weights that assume extreme values generate erratic causal estimates, an issue that increases with the number of treatments.

In our case, there is a limited number of treatments (three treatment statuses) and our weights, despite being close to 1 (table 2), are fairly concentrated in the same area between the three groups. Resultantly, the overlap assumption is met (figure 3).

Figure 3. Overlap of inverse-probability weighted propensity score



Source: Inapp PLUS 2018

4. Empirical results

4.1 Logistic regressions

Table 3 below reports the average marginal effects yielded by the bivariate regressions run. Overall, there does not appear to be significant mismatch as a function of one's citizenship (M1) or one's migration story (M2). There does appear to be a significant effect of informal networks on over-qualification.

As models 3 and 4 suggest, the use of networks to look for and find a job significantly decreases the probability of over-education; by 0.5 percentage point (p.p.) with the intensity of network use to look for a job, and by 8.4 p.p. where the use of network leads to a job.

The inclusion of covariates in models 5 to 10 (table 4) allows a more precise estimation of the net effect of being a foreigner and of networks. It confirms the absence of effect, on the whole, of being

a foreign citizen. If the coefficients are of greater magnitude (models 5 and 7 compared to model 1), they are not statistically significant.
Further breaking down the foreign category, it appears that the foreigners who grew up in Italy are less likely – by 3.8 to 5 p.p. (models 6 and 8) – to be over-qualified than their native counterparts. Conversely, there is no evidence that migrants who prevalently grew up abroad and arrived in Italy later on are more over-qualified than natives.

Table 3. Results of bivariate probit regressions. Models 1 through 4. Average marginal effects

	Model 1	Model 2	Model 3	Model 4
Foreign citizen	-0.0015 (0.010)			
Migrated		0.0039 (0.012)		
Grew up in IT		-0.0182 (0.017)		
Network-looking			-0.005*** (0.000)	
Network-finding				-0.0836*** (0.005)
N	29159	29153	26102	19194

Source: Inapp PLUS 2018
Note: standard errors in parentheses * p<0.1, ** p<0.05, *** p<0.01.

On a different note, the effect of informal networks is associated to a decrease in the probability of being over-educated. While looking for a job, a one point increase (on a 0-12 scale) of the intensity of use of informal networks translates into a 0.4 p.p. decrease in the probability of over-education. Considering the fact of finding one's job through informal networks, the probability of over-education decreases by 6.5 p.p.
The combined effects of migration status and the use of networks is computed through the introduction of an interaction between these two terms in model 6 and 8 (not reported). The interactions are not statistically significant and the predicted probabilities for the three categories do not significantly differ from one another to conclude to a differentiated effect of networks between natives, migrants and foreigners who grew up in Italy.
Interestingly, looking at models 9 and 10, which only consider migrants who grew up abroad, there appears to be no effect whatsoever of the length of stay (in contrast with Chiswick and Miller, 2009, and Dustmann and Van Soest, 2002) and of the area of origin (in contrast with Mattoo *et al.* 2008). With regard to networks, the effect is uncertain when it comes to looking for a job (model 9) whilst it appears less so when current occupation is found through networks (model 10); with a 7.8 p.p. decrease in the probability of over-education. To further test the results of the probit regression presented thus far, we use matching technique through propensity scores to correct the unbalances of our sample.

Table 4. Probit regressions, average marginal effects, Models 5 to 10

	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Foreign citizen	-0.0121 (0.011)		-0.0166 (0.014)			
Migrated		-0.0005 (0.014)		-0.0038 (0.017)		
Grew up in IT		-0.0381** (0.016)		-0.0503* (0.028)		
Network-looking	-0.0041*** (0.000)	-0.0041*** (0.000)			-0.0037 (0.003)	
Age	0.0003 (0.000)	0.0003 (0.000)	0.0005** (0.000)	0.0005** (0.000)	0.0052*** (0.002)	0.0043** (0.002)
Gender	-0.0556*** (0.004)	-0.0553*** (0.004)	-0.0543*** (0.004)	-0.0541*** (0.004)	-0.0664** (0.028)	-0.0909** (0.040)
Child(ren)	-0.025*** (0.004)	-0.0251*** (0.004)	-0.0233*** (0.005)	-0.0234*** (0.005)	-0.0423 (0.035)	-0.0653* (0.039)
Area Centre	0.018*** (0.005)	0.018*** (0.005)	0.0163*** (0.005)	0.0162*** (0.005)	0.051 (0.041)	0.0782** (0.038)
Area South	0.0098** (0.004)	0.0099** (0.004)	0.0085* (0.005)	0.0086* (0.005)	-0.0525* (0.031)	-0.0418 (0.049)
Major cities	0.0272*** (0.004)	0.0273*** (0.004)	0.0302*** (0.004)	0.0303*** (0.004)	0.068** (0.029)	0.0887*** (0.033)
Father's education	0.1183*** (0.005)	0.1183*** (0.005)	0.1029*** (0.004)	0.1029*** (0.004)	0.1081*** (0.032)	0.1023*** (0.033)
Work status	-0.0602*** (0.004)	-0.0602*** (0.004)			0.0196 (0.043)	
Tenure	-0.0034*** (0.000)	-0.0034*** (0.000)	-0.0034*** (0.000)	-0.0033*** (0.000)	-0.0008 (0.003)	-0.0034 (0.003)
Public	-0.0445*** (0.004)	-0.0446*** (0.004)	-0.0429*** (0.005)	-0.0429*** (0.005)	-0.1047** (0.047)	-0.0589 (0.054)
Network-finding			-0.0651*** (0.005)	-0.0654*** (0.005)		-0.0784** (0.036)
Length of stay					-0.0031 (0.002)	0.0007 (0.002)
Origin E. Europe					-0.0542 (0.054)	-0.0081 (0.053)
Origin N. America					0.0193 (0.139)	0.1628* (0.090)
Origin C. S. America					-0.0436 (0.058)	-0.0108 (0.059)
Origin Africa					0.0013 (0.072)	0.0584 (0.079)
Origin Asia Oceania					-0.0209 (0.133)	-0.0107 (0.116)
Origin other					0.042 (0.078)	0.0355 (0.065)
N	24384	24380	18468	18467	308	217

Source: Inapp PLUS 2018

Note: standard errors in parentheses * p<0.1, ** p<0.05, *** p<0.01.

4.2 Matching strategy

In order to test further the validity of our results, we implement a propensity score matching model to put foreigners and Italians on a par (see methodology section for more on this point). Subsequently, we differentiate between those foreigners who grew up in Italy and those who migrated there in order to ascertain the validity of the results presented in the previous section.

Firstly, we analyse the dichotomy foreigner-native. Once the group of foreigners and that of natives are attributed their propensity scores, we match them in different manners in order to obtain sounder results. Table 5 below reports the results. Overall, after having matched the observations, the effect of being a foreigner on the probability of mismatch appears somewhat clearer than previously estimated. The probit regression on the matched sample yields a positive 9 p.p. difference between natives and foreigner where they estimated a negative and statistically not significant effect on the overall sample. More specifically, whilst natives have, on average, a 14.2% probability of being over-educated; foreigners display a 23.4% probability. Matching the observations relating to foreigners to their close native neighbours, irrespective of the matching method, reveal a statistically significant difference ranging between 4.7 and 8.9 p.p. from one group to another.

Table 5. Estimation of the average effect on the treated (ATT) of being a foreigner: logistic, nearest neighbour, Kernel and radius matching estimations

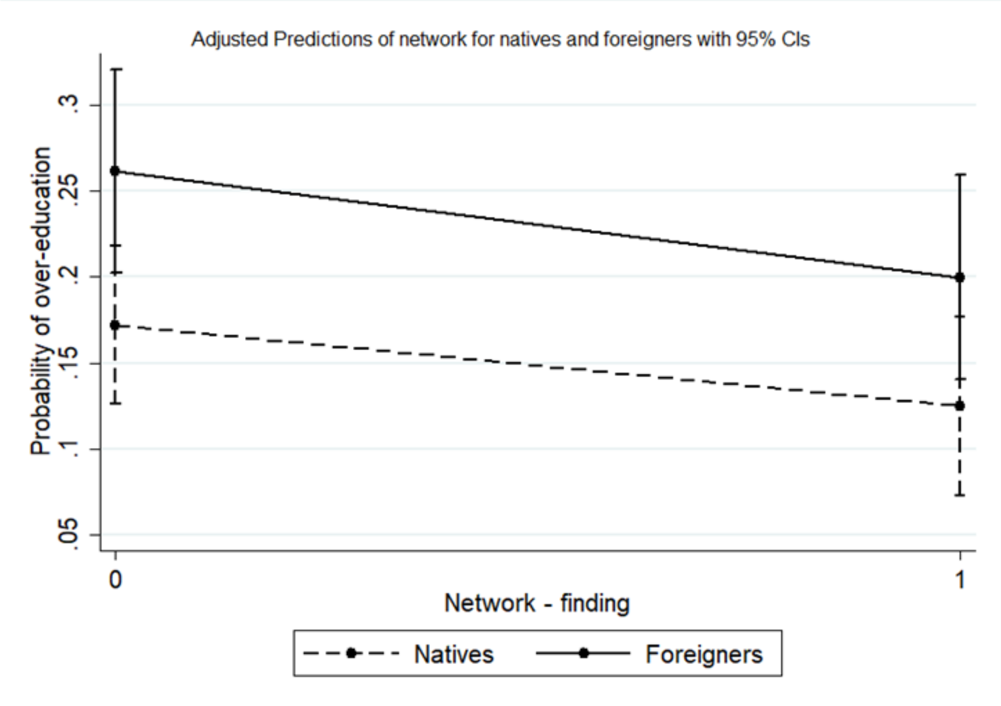
ATT	Probit model	Nearest neighbour	Kernel matching^{x}	Radius matching (0.1)	Probit model	Probit model
Foreign citizen	0.091*** (0.024)	0.069*** (0.023)	0.047** (0.022)	0.089*** (0.021)	0.091*** (0.026)	0.084*** (0.032)
Network-looking					-0.002 (0.003)	
Network-finding						-0.054* (0.032)

Source: Inapp PLUS 2018
Note: standard errors in parentheses * p<0.1, ** p<0.05, *** p<0.01; x: bootstrap std.err.

In a different fashion, considering the effect of informal networks on matched observations reveals that there is no significant (both statistically and substantively) effect of the intensity of informal network use on over-education even though there does appear to be an effect of networks onto mismatch when they lead up to employment. Interestingly, the effect is negative, meaning that finding employment through networks consistently decreases the probability of over-education by 5.4 p.p. (statistically significant at the 90% level). Figure 4, however, shows the breadth of the effect is no different for natives and foreigners as the slopes are very similar.

Now turning to the difference between types of foreigners, namely migrants and foreigners with a migration background, the results of the inverse-probability treatment weighting (IPW) confirm those presented above in terms of direction of the effect and statistical significance level. However, breaking down the foreign category into migrants and foreigners who grew up in Italy points to a notable difference between these two groups (table 6). Namely, migrants are 6.6 p.p. more likely to be over educated than natives and 15.5 p.p. more likely to be so than foreigners who grew up in Italy. Reversely, there does not appear to be any difference between foreigners who grew up in Italy and natives (coefficient of limited magnitude and not statistically significant).

Figure 4. Overlap of inverse-probability weighted propensity score



Source: Inapp PLUS 2018

Table 6. Estimation of the average effect of migration and migration background: multinomial logistic estimation

Average treatment effect on the treated	**Coefficients**
Migrated vs. natives	0.0655*** (0.014)
Migration background vs. natives	0.0241 (0.047)
Migrated vs. migration background	0.155*** (0.053)

Source: Inapp PLUS 2018
Note: standard errors in parentheses * p<0.1, ** p<0.05, *** p<0.01.

The estimates provided thus far converged towards a greater probability of over-education for the foreigners who migrated than for natives or foreigners who grew up in Italy. It remains to be seen whether the use of informal networks plays a role in it. Table 7 reports our estimates. Overall, with refined models that account for foreigners' background, it appears that the use of informal networks significantly decrease over-education. On average, the intense use of networks to look for a job is associated with a 0.6 p.p. lower probability of over-education, a limited coefficient in width but consistent across categories. In the same vein, people who have found their current job through informal networks are 8.1 p.p. less likely of being over-educated.

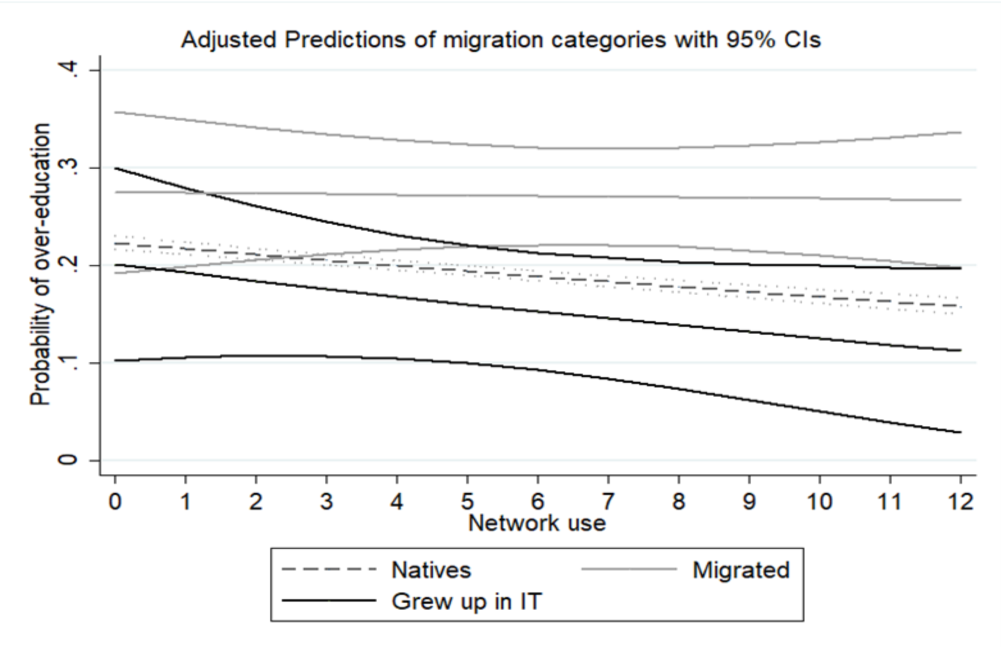
Table 7. Estimation of the effect of informal networks. Logistic regression with inverse probability weighting, average marginal effects

Average treatment effect on the treated	Probit model 1	Probit model 2
Migrated	0.0881*** (0.026)	0.0827*** (0.032)
Grew up in IT	-0.0339 (0.031)	-0.0433 (0.038)
Network-looking	-0.0055*** (0.001)	
Network-finding		-0.0811*** (0.006)

Source: Inapp PLUS 2018
Note: standard errors in parentheses * p<0.1, ** p<0.05, *** p<0.01.

However, said effect does not appear to vary much between categories. When considering the intensity of network use to look for a job, the effect is always negative, more so for natives and foreigners who grew up in Italy, while it is only slightly negative for migrants. Figure 5 illustrates that[9].

Figure 5. Effect of migration categories at different levels of networks' use. Predicted probabilities

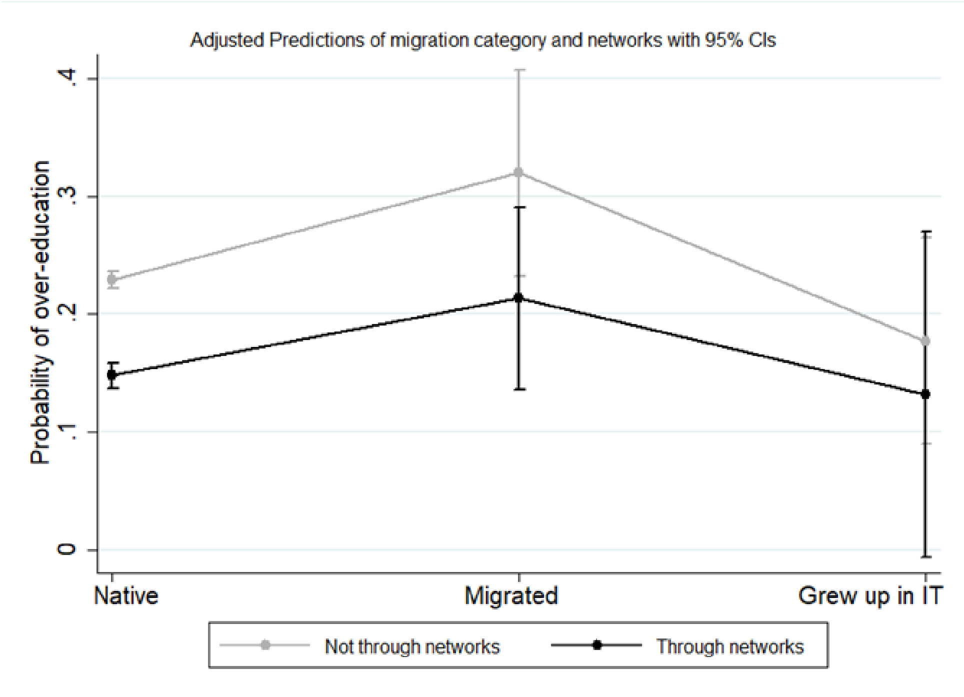


Source: Inapp PLUS 2018

[9] For a clearer idea of this effect, probit model 1 was run again with an interaction term. We do not report the coefficient for ease of reading. Not that the interaction term in the probit regression is not statistically significant but plotting the predicted probabilities show that the effect is not significantly different between natives and foreigners who grew up in Italy while it is with respect to the third category; all the more so as use of networks increases.

If, instead, we consider the instances in which respondents reported having found their current employment through networks, the effect of the latter does not vary from one category to another as the confidence intervals for our two categories of interest overlap significantly. Figure 6 illustrates that[10].

Figure 6. Effect of migration categories and network leading to employment. Predicted probabilities



Source: Inapp PLUS 2018

5. Discussion and concluding remarks

The results presented above propose a picture in shades that this section aims at discussing. On the one hand, the first empirical approach (probit models on the whole sample) consistently underlines the negative effect of networks on over-education; i.d. the use of networks to look for a job and cases in which a job was found through networks reduces the probability of over-education. It however fails to capture an effect of migration status onto our dependent variable. On the other hand, the second approach produces more nuanced results with a clear effect of the migration status and a consistent effect of networks when we dissociate migrants from foreigners with a migration background.

Fundamentally, part of our contrasting results is due to the fact that the two approaches endorsed follow two different logics. The use of regression models on sample data aims at producing reasonable inferences as to what occurs in the population as a whole. They are said to have internal and external validity. Consequently, statistically significant coefficients suggest that there is a good chance that the

[10] As for the previous figure, we re-run probit model 2 with an interaction effect, of which we do not report the results for ease of reading. Note that the interaction term is not statistically significant.

results obtained in the sample are close to what would be observed in the population. Conversely, counterfactual approaches seldom allow inferences on the population as a whole but ensure a sounder comparison between groups by controlling for self-selection into one group or another. Put differently, they allow a comparison between different groups at parity of relevant observables, thus reinforcing the internal validity of our analysis.

Considering the composition of our sample and the under-representation of foreigners, inferences regarding the difference between foreigners and natives ought to be presented with caution. Because only 2.4% of our sample concerns foreigners, the estimates we produce on covariates are overdetermined by the characteristics of the native population (as the descriptive statistics in table 1 bear witness), thus undermining the external validity of the results. It remains, however, interesting to take advantage of the wealth of information available to assess the role of networks on over-qualification, an effect that is also confirmed by the counterfactual models applied subsequently. Differently, the estimates produced following the counterfactual methods employed produce sounder results by correcting our unbalanced sample. They however yield results that are internally valid but that cannot safely be generalised to the whole population.

Education-occupation mismatch is an issue that undermines the efficient allocation of human resources in the labour market, particularly in Italy (Pizzuti 2006). Whilst it regards the population as a whole, evidence in a range of OECD countries tends to suggest that it affects migrants more than natives. Different explanations were put to the test over the years with a growing attempt to capture the effect of informal networks onto over-education. Presumably, resorting to those networks would undermine the ability of workers to match their qualification with their job. Interestingly, no studies that we are aware of has aimed at studying the effect of networks on migrants' over-education in Italy. Yet, Italy is a country for which there is quite some evidence on the relationship between informal networks and education-occupation mismatch.

This article is an attempt to fill this gap. It contributes to the specialised literature in three ways. First, we look into the Italian case, a country that has seen its foreign population growing at a fast pace over recent years. Second, we use a unique database that allows us to rely on a clear, self-declared specification of the use of networks instead of building a proxy. In so doing, our estimates are more direct and more interpretable than that of other studies. Third, we propose to differentiate the effect of networks between foreigners who grew up in Italy and foreigners who migrated later on in their life and who allegedly face more hardship in integrating the Italian labour market. We produce evidence by using two different methodological approaches. The first one consists in a series of regressions on the whole sample; an approach that produces estimates that are both internally and externally valid. The second one aims at correcting our unbalanced sample with matching and weighting methods. In this manner, we decrease the external validity of our results whilst proposing sound estimates.

We find that there is evidence of a difference in over-education between foreigners and natives; a difference that is clearer when we distinguish between the foreigners who grew up in Italy and those who migrated later in their life. The former are undistinguishable from natives whilst the latter tend to be significantly more over-educated. As for the effect of networks, it appears to be consistent across our three groups: irrespective of one belonging to one group or another, the use of networks consistently decreases over-education.

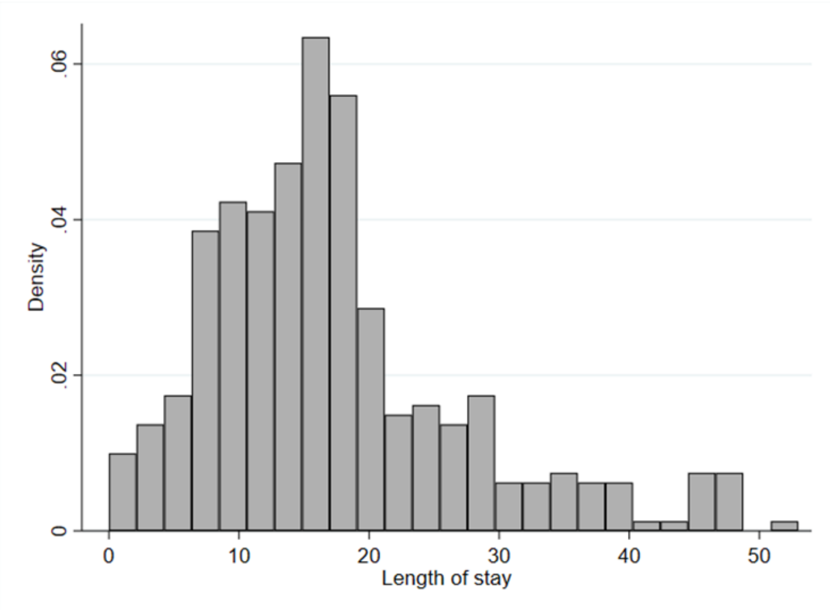
Appendix

Data

We use the data of the IIX edition 2018 of PLUS (Participation, Labour and Unemployment Survey), a survey on the Italian population in working age (18-74 years old) conducted every second year. PLUS 2018 data was collected in late 2018 and released in the first half of 2019. It counts 45,000 individuals. A crucial characteristic of this dataset is the absence of proxy interviews: only survey respondents are included, thus reducing measurement error and partial non-responses. The questionnaire was submitted to a sample of residents, according to a stratified random sampling over the Italian population. PLUS also provides individual weights to account for non-response and attrition issues generally affecting sample surveys. Similarly to other empirical articles using the same survey (see Meliciani and Radicchia 2011, 2016; Clementi and Giammatteo 2014; Filippetti *et al.* 2019), all descriptive statistics and estimates reported in this analysis are weighted accordingly. For more information in this respect, see www.inapp.org.

As explained in the main text, the type of agglomeration in which the respondents reside may affect their work prospects. Urban environments likely offer more opportunities than rural ones. Accordingly, the type of agglomeration was introduced in all our models. It has, however, been categorised differently from one approach to the other. In the first approach, i.e. probit regressions, we introduced a dummy variable separating agglomerations with less than 50,000 inhabitants (small cities) and more than 50,000 inhabitants (big cities). In our matching approaches, because the pool of counterfactuals allowed it, we introduced more precise categories. Namely, we considered five categories: up to 5,000; from 5,000 to 20,000; from 20,000 to 50,000; from 50,000 to 250,000; more than 250,000 inhabitants.

Figure A1. Density histogram of foreigners' length of stay in Italy



With regard to the individuals with foreign citizenship, they are distributed according to their regions of origin as follows: 51% are from Eastern Europe, 19% are from Central and South America, 10% are from Africa, 2% are from North America and another 2% are from Asia and Oceania; 14% of them have preferred not to reveal their area of origin. Of the non-natives, 68% are migrants whilst 32% are second generation migrants. With regard to foreigners' length of stay in Italy at the time of the survey, they have spent on average about 17 years in the country, with a distribution positively skewed, which makes a lot of sense given that Italy has only recently (comparatively to other EU countries) become a destination country (figure A1). Nonetheless, about 25% of the foreign citizens in our sample have spent more than 21 years in Italy with a maximum of 53 years.

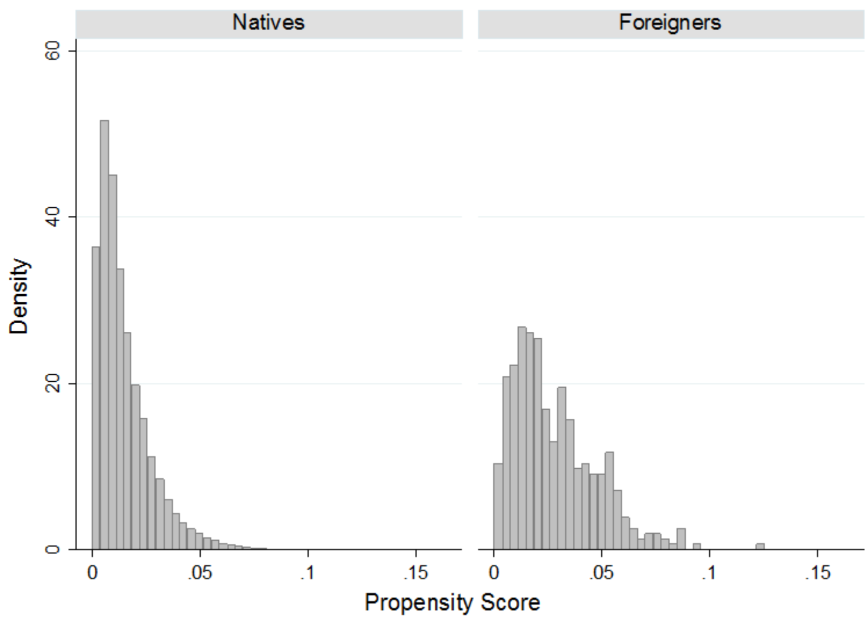
Method

As stated in the main text, our empirical strategy is twofold. On the one hand, we use probit regressions to test our hypotheses. On the other hand, we resort to counterfactual analysis methods to compare our different groups in a way that counterbalances the biases in our sample. Whilst the first approach is straightforward, the second requires some more explanations. Hereinafter, we provide some elements of method as well as the results of our robustness tests in order to help the reader assess the soundness of the empirical evidence presented.

Propensity score matching (PSM)

The calculation of propensity scores yields sound results that may be assessed through comparison between foreigners' and natives' scores. Figure A2 shows a rather homogeneous distribution of the propensity scores between the two groups, thus guaranteeing the accuracy of matching methods as comparison can be restricted to common support.

Figure A2. Density histograms of the propensity scores for foreigners and natives

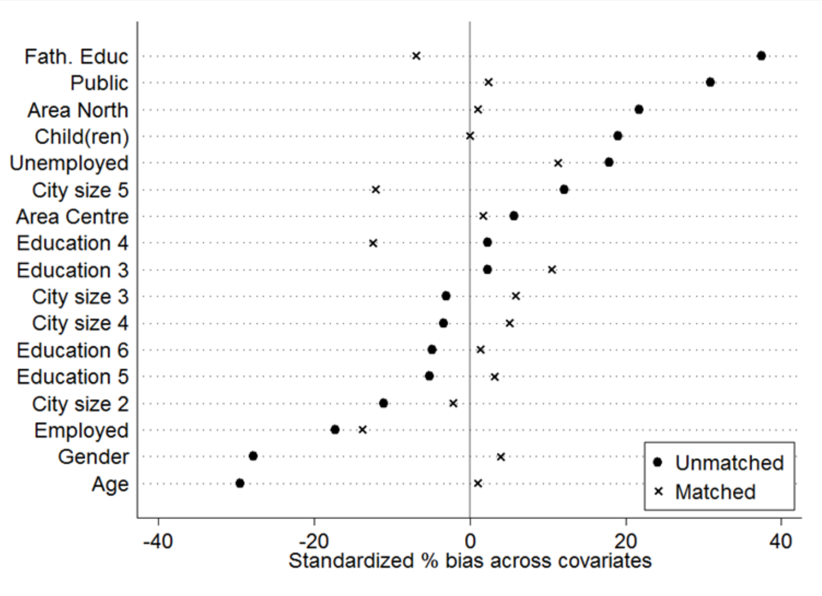


Our tests suggest that the balancing property is met. Table A1 and Figure A3 show a significant bias correction from the unmatched to the matched sample, thus suggesting that the propensity score does a good job at balancing observations across variables by significantly reducing the bias present in the sample.

Table A1. Balancing property for the matched and unmatched samples and bias correction

Variable	Matching status	Mean		Bias	
		Treated	Control	% Bias	% Reduction bias
Gender	Unmatched	0.309	0.443	-27.8	
	Matched	0.309	0.290	4.0	85.6
Child(ren)	Unmatched	0.681	0.590	19.0	
	Matched	0.681	0.681	0.0	100.0
Public sector	Unmatched	1.859	1.735	31.0	
	Matched	1.859	1.849	2.4	92.2
Area North	Unmatched	0.576	0.468	21.7	
	Matched	0.576	0.571	1.0	95.6
Area Centre	Unmatched	0.235	0.212	5.6	
	Matched	0.235	0.228	1.7	69.4
Age	Unmatched	41.94	45.462	-11.1	
	Matched	41.94	41.815	-2.1	80.7
City size 2	Unmatched	0.254	0.304	-8.2	
	Matched	0.254	0.264	3.5	57.8
City size 3	Unmatched	0.156	0.167	-3.0	
	Matched	0.156	0.134	5.9	-93.5
City size 4	Unmatched	0.170	0.183	-3.4	
	Matched	0.170	0.151	5.0	-49.0
City size 5	Unmatched	0.194	0.149	12.1	
	Matched	0.194	0.240	-12.1	-0.2
Education 3	Unmatched	0.161	0.152	2.3	
	Matched	0.161	0.122	10.6	-365.0
Education 4	Unmatched	0.496	0.485	2.3	
	Matched	0.496	0.559	-12.5	-433.5
Education 5	Unmatched	0.290	0.314	-5.2	
	Matched	0.290	0.276	3.1	39.6
Education 6	Unmatched	0.031	0.040	-4.8	
	Matched	0.031	0.029	1.6	73.0
Fath. Education	Unmatched	0.518	0.335	37.5	
	Matched	0.518	0.552	-6.9	81.6
Employed	Unmatched	0.628	0.709	-17.2	
	Matched	0.628	0.693	-13.8	20.0
Unemployed	Unmatched	0.245	0.172	17.9	
	Matched	0.245	0.199	11.3	37.1

Figure A3. Propensity scores' bias correction after matching (%)



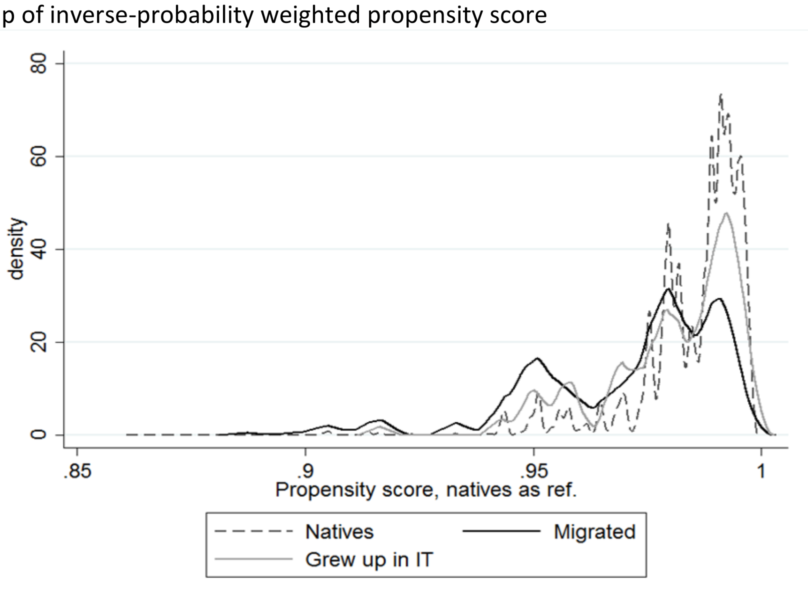
Inverse-probability treatment weighting (IPW)

With regard to IPW, the conditions for its validity are chiefly two: the size of the weights; and their overlap. Weights that assume extreme values generate erratic causal estimates, an issue that increases with the number of treatments. In our case, there is a limited number of treatments (three treatment statuses) and our weights, despite being close to 1 (table A2), are fairly concentrated in the same area between the three groups. Resultantly, the overlap assumption is met (figure A4).

Table A2. Summary statistics of propensity scores

Variable	Obs.	Mean	Std. Dev.	Min	Max
Propensity score	36,912	0.9858	0.0120	0.8619	0.9986

Figure A4. Overlap of inverse-probability weighted propensity score



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