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Italy: No country for highly educated immigrant workers

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Abstract

This paper estimates the returns of education on the first generation of immigrants in Italy and measures the education pay gap between immigrants and natives. The analysis, drawn on two comparable cross-sectional surveys conducted by the Italian Institute of Statistics in 2009, shows that an immigrant with a tertiary education degree has a 20% increase in hourly wage compared to immigrant workers with a postsecondary education degree. The absence of a legal recognition of the education degree does not produce any return to education for the immigrants. Relevant differences in educational returns are found between immigrants and natives, with an education wage gap of approximately 61%. These results shed new light on the two channels that may contribute to the wage gap between highly educated immigrants and natives in Italy. The first channel moves behind the heterogeneity of highly educated immigrants with respect to their education quality and comparability and on relevant differences in the formal process of recognition of the education degree. The second channel is linked to the job mismatch of the immigrant workforce.

Keywords: Immigrant pay gap, High education, Overeducation.
JEL Classification: J15, J24, J31.

1 Introduction

In recent decades, immigration has become one of the most prominent public policy issues in several European economies. Public concern and policy attention have been mainly focused on forced migration, cooperation over asylum and the prevention of massive immigration across European borders. At the same time, European countries are involved in the global competition for highly skilled immigrants. Attracting a high-skilled workforce from abroad is widely perceived as the major strategy to address the demographic transformation in these countries and to keep knowledge-based economies competitive (OECD and European Union, 2016). Indeed, with low birth rates, European society is ageing quickly and is likely to face a severe shortage of a young qualified labour force in the near future.[1] Whereas some countries, such as

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[1]Low fertility reduces the rate of scientific and other innovations since innovations mainly come from younger individuals. Younger individuals also are generally more adaptable, which is why new industries, such as high-tech startups, generally attract younger workers who are not yet committed to older and declining industries (Becker, 2013).

Germany, Sweden and Finland, are governing this demographic transformation, substantially changing their immigration policies[2], other southern European countries, such as Italy, Spain, Portugal and Greece, are at the margin of global competition (OECD and European Union, 2016; Zanfrini et al., 2015).[3] These latter countries may not appear on the radar for high-skilled job searches and may be less attractive than other countries due to wage levels, facility of integration, family and cultural aspects (Peixoto et al., 2012).

Immigrants do not represent a random sample of the population of the origin country, and the choice to migrate is crucially determined by differences in the expected relative payoffs between the origin and host countries (Borjas, 1987). Indeed, whenever relative returns to education are lower in the origin country, immigrants are likely to self-select from the right tail of the skill distribution. By contrast, whenever relative payoffs are higher in the country of origin, immigrants self-select from the left tail of this distribution. This implies a selection in migration among immigrants showing that highly educated migrants do not have any incentive to move in a country where their human capital[4] is not transferable or where their wage does not reflect their level of education. Indeed, as noted by Chiswick and Miller (2009), when immigrant human capital is not fully transferable to the host country, immigrants will be more likely to work in jobs where their level of schooling is higher than the usual level of schooling of natives. In this case, it arises a job mismatch that is mainly caused by imperfect information in the labour market, as workers take up jobs for which they are overeducated (Chiswick and Miller, 2009).[5] In contrast, the lack of integration of immigrants in the host labour market may reflect differences in the quality and comparability of the acquired human capital within the host labour market. In the latter case, wage returns to education significantly differ across home countries, and the level of economic development of these countries positively affects the transferability of studies completed abroad (Friedberg, 2000).

Immigrants' choice is still influenced by immigration policies, both general and specific to skill transferability and selection. Once at the destination country, these policies have a long-lasting effect on labour market outcomes, accommodating or impeding the correct matching of skills (Aleksynska and Tritah, 2013). In this context, the implementation of instruments envisaging well-designed processes of formal recognition is found to be relevant for a more careful recruitment of human resources and a better capitalisation of migrants' human capital. In contrast, in many countries, the process of formal recognition is complex, costly and time-consuming, and risk discourages extra-EU citizens from the outset. This is particularly true in national contexts; due to an incomplete legal framework and to inefficient operational mechanisms, the formal recognition of the education degree appears to be essentially impossible for those who do not fall into categories with privileged channels of recognition (Lodigiani and Sarli, 2017).

This paper estimates the returns of high education on the first generation of immigrants in Italy by quantifying the pay gap between immigrants and natives. Italy is an interesting case to study for several reasons. First, during the 2000s, Italy was exposed to a very fast and large wave of immigration, mostly low educated and coming from developing countries (Bratti and

[2]In these countries, recognition of foreign qualification, lifelong learning, and diversity management in the workplace are at the forefront of the policy agenda.

[3]These countries resort to mass regularisation aimed at legalising migrant workers who had acceded to the market without authorisation. Immigrants are often employed in a few specific sectors, usually in less stable, lower-paying and less protected jobs, which correspond to the least-protected parts of ac highly segmented labour market (Peixoto et al., 2012).

[4]In line with the prevailing literature, we use human capital as a synonym for high education. Nevertheless, we are aware that human capital is not only the result of formal education but also depends on the increase in knowledge through learning-by-doing. For this reason, in the empirical analysis, we will control for the experience of the worker and for the different value in the host labour market of the experience acquired in the origin and in the host country.

[5]As shown by Aleksynska and Tritah (2013) 22% of immigrants face overeducation in Europe.

Conti, 2017; Pieroni et al., 2022). Indeed, the political instability of North African and Middle Eastern countries and the extensive Italian welfare system have fed important waves of young and low-educated immigrants (Bratti and Conti, 2017). Second, Italy's total fertility rate is one of the lowest in the world, and as a result of this low fertility, the Italian population is expected to sharply decline. Third, as stated by Bonatti et al. (2019), in Italy, immigrants' incomes are concentrated in the lower tail of the income distribution, and the average annual earnings of extra-EU workers are 35% lower than the average annual earnings of natives. Finally, in Italy, the education degree is mandatory to access specific high-wage jobs[6] and the formal recognition of foreign education is regulated with great caution by a very complex legislative framework. Indeed, the system of recognition is based on a case-by-case approach, and procedures vary and are entrusted to different bodies depending on how the foreign qualification is to be utilised (Zanfrini et al., 2015).

The analysis is drawn on two comparable cross-sectional surveys financed by the Italian Minister of Labour and Social Policies and conducted by the Italian Institute of Statistics in 2009. To estimate the education returns, we use the highest education level of the worker instead of the number of years spent in education. Indeed, as stated by Brunello et al. (1999), in the Italian education system, one additional investment in education that does not lead to the award of a degree might not grant additional labour market returns. This means that the accumulation of human capital is not necessarily a smooth linear process and the returns to education could not be the same for a given number of years.[7] We constrain the analysis only to non-compulsory school and, to identify the returns to education, we compare workers with a postsecondary degree to those with a tertiary education degree.[8] We justify this choice by suggesting that, to measure the additional investment in education, in line with Becker's model (Becker, 1975), we need to take into account only investment choices that can be taken freely.

The main identification issue arising from estimating the educational return in the immigrant population is linked to the mediating effect of formal recognition policies. Indeed, a worker with a not-recognised education degree would not experience any premium in the additional investment on education acquired in the origin country. To address this issue, we propose an identification based on a front-door criterion (Pearl and Mackenzie, 2018) and estimate the effect of education on hourly wages explicitly considering the mediating effect of formal recognition on the education degree.[9] We then compare these results to those applying an instrumental variable approach to account for the nonrandom selection of immigrants and for differences in unobservable abilities. In the latter case, we use, as excluded instruments, two variables accounting for the enlargement of the European Union to Eastern countries that occurred in 2004 and 2007. These enlargement policies have increased the probability of attracting highly educated workers to new EU members. Indeed, after becoming an EU member, the formal recognition of the education degree is regulated by the Lisbon Treaty, which simplifies the bureaucratic procedure to obtain the legal recognition of the education degree in the host country. An IV approach is still applied to the Italian population to account for unobservable abilities. In this case, we exploit the exogenous variation in school achievement induced by the

[6]By Italian law, the education degree is mandatory to access high-wage jobs in the public sector and also is relevant in the private sector. Indeed, in the private sector, the task of a job and the wage also are determined by the employer on the basis of the education degree of the employee. For a further discussion about the positive relationship between education and earnings, see, for example, ISTAT (2018).

[7]This shortcoming is relevant for Italy in two respects. First, in Italy, the education degree has legal value and is mandatory for specific jobs. Second, Italy has a massive dropout rate, and hence, the number of years spent in the educational system might not describe the human capital acquired by the individual.

[8]The length of compulsory education varies country by country. Hence, to have two comparable groups, we extend the analysis to postsecondary education when immigrant workers are accounted for.

[9]Whereas the back-door criterion blocks all the noncausal information that is included in the vector of observable characteristics, the front-door exploits the outgoing information included in a specific variable (i.e., the formal recognition of the education degree) to derive a causal estimator.

1962 mandatory middle school reform that increased the average years of schooling and the school attendance rates (Brandolini and Cipollone, 2002) and the exogenous variation induced by Law 910 of December 1969 that extended the possibility of enrolment in college to individuals with completed secondary education, independent of the track (general or vocational) chosen in secondary school (Brunello et al., 2000).

Our results show that an immigrant with a tertiary education degree has a 20% increase in hourly wage when compared to workers with a postsecondary education degree. This result is valid only when we account for highly educated workers with a formal recognition of the education degree. Indeed, the absence of such recognition does not produce any return to education. Furthermore, relevant differences in educational returns are found between immigrants and natives, since the return of high education in the Italian population is approximately 51%. That is, we find a wage gap of approximately 31 pp (approximately 61%) between immigrants and natives. Furthermore, when we isolate only migrants coming from those countries with a GDP higher than the sample median, to reduce the differences in the quality and comparability of the acquired human capital within the host labour market, the education premium of the immigrant workforce increases (approximately 33%) but remains significantly different from that of the natives. These results shed new light on the two channels that may contribute to the wage gap between highly educated immigrants and natives in Italy. The first channel is linked to the quality and comparability of the foreign degree and to the relevant differences in the formal process of recognition of the foreign education degree. The second channel is linked to job mismatch and the overeducation of the immigrant workforce.

The outline of the paper is as follows. In Section 2, we present the data used and the descriptive statistics. In Section 3, we study identification and estimation issues. In Section 4, we show the empirical results of the analysis. Finally, we conclude in Section 7.

2 Data and variables

The empirical analysis is based on two comparable surveys financed by the Italian Minister of Labour and Social Policies and conducted by the Italian Institute of Statistics in 2009, or the Income and Living Condition of Household with Foreigners (ILCEF) and the Italian wave of the European Social Survey (IT-SILC).[10] More specifically, the ILCEF, based on a sample of 6,000 resident households in Italy with at least one foreign member, made use of the same methodological tools used for the IT-SILC (ISTAT, 2011).

The sample consists of employees aged 15-64 years. We remove from the samples workers still in the educational system and those retired in the year of the survey. When the ILCEF is accounted for, we then constrain the analysis only to the first generation of immigrants. Indeed, the information available in the dataset concerning the second generation is too limited to perform an analysis on this segment of the immigrant population. Using this structure, we end up with two samples, including approximately 5,000 immigrants and 11,500 Italians. As an outcome variable, we refer to the gross hourly wage, obtained by dividing yearly income from employment by the number of hours worked in the year.

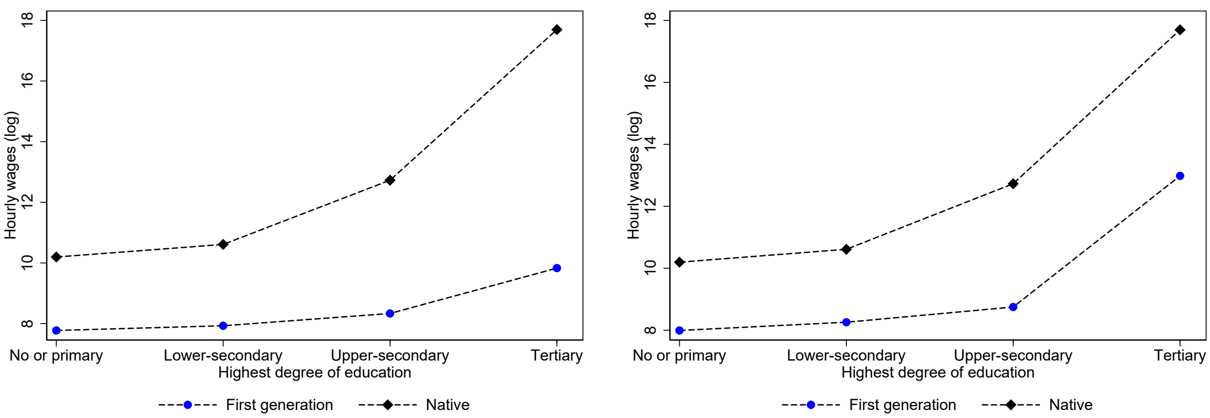
Table A1 (Appendix A) gives the descriptive statistics of the main variables, comparing the immigrants with the natives. Focusing on the pattern of educational dummies, it can be observed that the share of workers with tertiary education is unbalanced in favour of natives. In this respect, we find that workers with a tertiary education degree are only approximately

[10] To date, to our knowledge, there are no nationwide longitudinal surveys in Italy that include specific information on migrants. The only other available survey is the Conditions and Social Integration of Foreign Citizens, which was conducted between 2011 and 2012 and published in 2014. The information of this survey is not considered since it is not comparable to the European Social Survey (IT-SILC) and because the survey does not include information on incomes.

9% in the immigrant population, whereas they represent approximately 17% of Italian workers. Furthermore, the immigrant population is overrepresented in temporary and part-time jobs and is mainly employed in the private sector.[11]

Table A2 (Appendix A) reports specific variables used in the analysis of the education premium of the immigrants. Following Friedberg (2000), we introduce the experience acquired abroad, since in this case, it also could be evaluated differently than the experience acquired in the host labour market. Then, following Pieroni et al. (2022), we introduce the age at immigration and the proximity to Italian of the native country language to account for the linguistic proficiency of the employee.[12] Furthermore, we introduce a categorical variable disentangling the main reason to migrate and a variable to control for the migration plans (i.e., Do you want to leave Italy?). These variables control for the aptitude of the migrant to be integrated into the labour market of the host country and for their desire to remain in that country. Indeed, as stated by Pieroni et al. (2022), Italy could represent only a transitory country for high-skill immigrants, and hence, immigrants could be more keen to accept jobs for which they are overeducated to reach their final destination.

Figure 1: Conditional expectation functions, hourly wages



(a) All degrees

(b) Legally recognised degrees

Notes: Recognition of qualifications is summarised in a binary variable: 0 when the worker has an unrecognised qualification, is waiting to obtain the recognition or has never applied for it, and 1 otherwise.

We complete the list of variables by accounting for the formal recognition of the education level. In Italy, foreign education degrees have no legal value, and hence, migrants need to obtain a formal legal recognition of the foreign title to use it in the labour market. Title recognition is mandatory to apply for public jobs and to access high-wage jobs in the private sector. The relevant regulation applied to the formal recognition of the education degree of European citizens is based on the 1997 treaty (treaty of Lisbon) ratified in Italy by Law 148/2002. The Lisbon Treaty simplifies the bureaucratic procedure to obtain the legal recognition of the education

[11]We do not consider, in the list of covariates, the occupation variable disentangling blue collars, white collars and managers and the International Classification of Occupations (ISCO). Indeed, these variables may be bad controls, since the higher the education title is, the higher the probability of having better occupations (Angrist and Pischke, 2008).

[12]To account for linguistic proximity, we adopt the index proposed by Adserà and Pytliková (2015) and apply it to the Italian case by Pieroni et al. (2022). Hence, we define a linguistic distance index using the classification of the distribution of country pairs by the Italian linguistic proximity index summarised in a binary variable: 0 when a linguistic distance is at least of the second level of the linguistic family tree compared to the Italian language, which identifies a greater linguistic distance, and 1 when there is a nonsignificant linguistic distance.

degree in each European country. In contrast, the recognition for extra-EU migrants is mainly based on bilateral agreements, not covering all the world countries. With respect to extra-EU migrants, the relevant regulation is based on the 1976 international treaty (treaty of Nice 1976), ratified by the Law 965/1980, which specifies privileged channels of recognition for migrants coming from Arab and Mediterranean countries. Other bilateral agreements have been signed between Italy and Argentina, Australia, China, Cyprus, Ecuador, former Yugoslavian countries, Malta, Mexico, the United Kingdom and Switzerland. In these latter cases, the outcome of the recognition process is uncertain, depending on more or less well-defined procedures of formal evaluation of their previous training and professional experience or on tests assessing migrants' competence.

The stringency of the requirements to obtain legal recognition of the education title is shown in Table A2 (Appendix A), where it is reported that only approximately 14% of immigrant workers have a recognised title, whereas approximately 18% of migrants have not received that recognition. It is important to note that the great majority of migrants do not apply for a degree recognition (approximately 68%), testifying that this is a major obstacle for workers to use their education in Italy. This statement is further clarified in Figure 5, where we report the conditional expectation functions (CEFs) by the education degrees[13], comparing the immigrants with the natives. When we consider both the recognised and the unrecognised degrees (Panel a), it seems that, moving from postsecondary to tertiary education, there is only a slight change in immigrants' hourly wages. In contrast, as expected, this change is evident in the sample of natives. Nevertheless, when we explicitly consider only recognised education degrees (see Panel b of Figure 5), we show that the return of tertiary education, in the migrant sample, is coherent with that of natives, even if the wage gap remains relevant. This corroborates the idea that the legal recognition of the education degree mediates the effect of education on wages, since it defines two different trajectories for the educational premium in the immigrant population. In the following analysis, recognition of qualifications is summarised in a binary variable: 0 when the worker has an unrecognised qualification, is waiting to obtain the recognition or has never applied for it, and 1 otherwise.

3 Identification

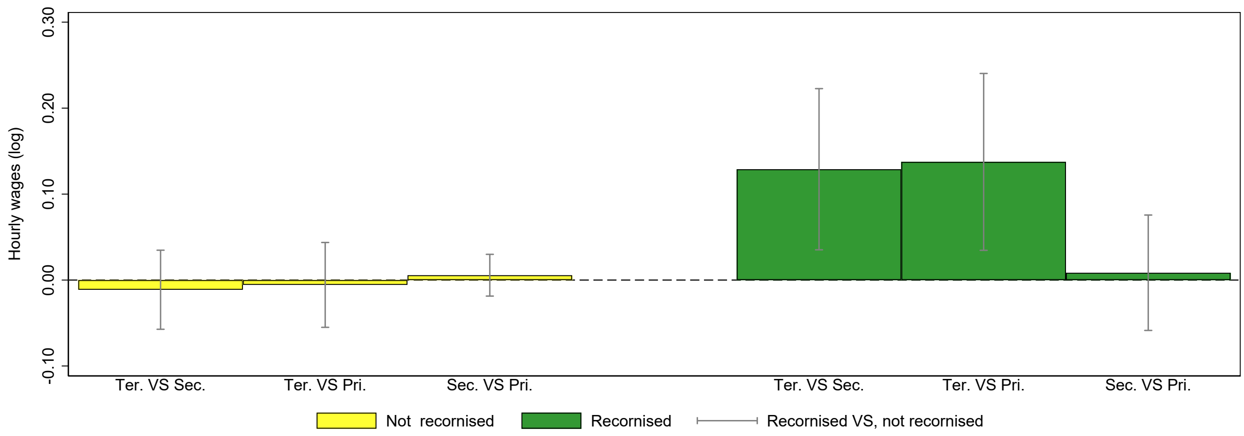
In this section, we propose an identification strategy to estimate the returns of formal education on hourly wages for immigrants and natives. Our first goal is to show that the absence of returns of education, shown in Panel (a) of Figure 5, can be fully explained by the fact that we were comparing two unbalanced groups by considering those workers with an unrecognised education degree in the CEF (see Panel b). This statement is further clarified in Figure 2, where we report the marginal effects by the formal educational degree, distinguishing between immigrants with an unrecognised and a recognised title.

As depicted by the figure, immigrants with an unrecognised title show no differences when we compare postsecondary and tertiary education or when we extend this comparison to primary education. In contrast, when only recognised titles are considered, we find that the higher the education title is, the higher the increase in hourly wages.

Based on this evidence, in Figure 3 we present the direct analytical graph (DAG) describing the proposed identification structure. As shown by the first panel of the figure, the causal path linking education (ED) and hourly wages (W) is mediated by the legal recognition of education title (REC). Hence, the use of a back-door criterion, blocking the indirect path involving the vector of observable variables X, is not sufficient to causally interpret the path

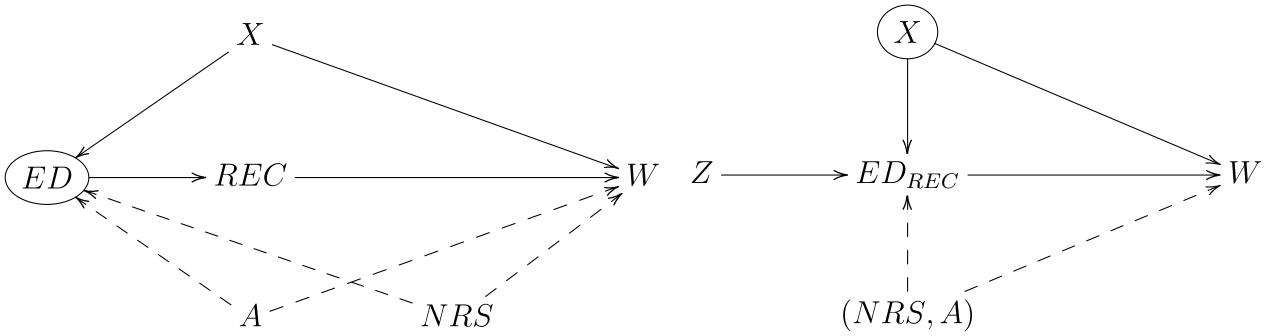
[13]The conditional expectation is the expected value of hourly wages, computed with respect to a conditional probability distribution of the education degrees, and is formally defined as $E(W_i|ED_i)$.

Figure 2: The migrant pay gap by education and formal-recognition status



Notes: Marginal effects are calculated through OLS regression, including the entire set of covariates reported in Tables A1 and A2. Clustered robust standard errors are used to obtain 5% confidence intervals. We omit the graphs comparing noneducated workers to save space.

Figure 3: DAG: identification of migrants' educational wage premia



$ED \to W$. This finding also remains valid when we consider a more realistic DAG, introducing two unobservable confounders or unobservable abilities (A) and the nonrandom selection of immigrants (NRS). In turn, this implies that the average treatment effect, capturing the causal link between high education and wages, is not identified. In contrast, if we suppose that there are no unblocked back doors in the path $ED \to REC$ or in the path $REC \to W$, we can apply a front-door criterion, identifying the effect of education on hourly wages. As shown by Pearl and Mackenzie (2018), in this case, we estimate the effect of education on wages explicitly considering the mediating variable REC.[14] We can apply the front-door criterion running the system of equations:

$$\begin{cases} W_i & = \beta_0 + \beta_1 ED_i + \beta_2 REC_i + \epsilon_i \\ REC_i & = \gamma_0 + \gamma_1 ED_i + \omega_i \end{cases} \tag{1}$$

were , following Bellemare and Bloem (2019), the system of equations is estimated through seemingly unrelated regression (SURE) and where the average treatment effect (ATE) is estimated through the formula $ATE = (\beta_2 \times \gamma_1)$.[15] Furthermore, looking to the DAG, we notice

[14] In this case, the use of an interaction between the mediating variable and the endogenous variable is not sufficient to block all the back doors in the path $ED \to W$.

[15] Following Giles (1982), the coefficient γ_1 is obtained by the formula $\gamma_1 = exp[\hat{\gamma_1} - 1/2V(\hat{\gamma_1})]$. The adjustment is needed since, in the second equation of the system described in equation 1, we regress a dummy variable ED_i on the dummy variable REC_i. In this case, the coefficient γ_1 is obtained by using a a Taylor expansion.

that if the front-door criterion holds, conditioning on ED is sufficient to block all the indirect links from REC to W and to causally estimate the path $ED \rightarrow REC \rightarrow W$. We can justify this statement suggesting that when we mediate the effect of education with the legal recognition of the education title, we are considering two groups that may be balanced with respect to observable and unobservable confounders. Indeed, in this case, in the counterfactual, workers with a tertiary education degree that is unrecognised also are included, implying that the unobservable abilities of the treatment and control groups may be similar in that respect. A related argument also can be used when we consider the second source of bias, enlightened by the economic literature, or rather the nonrandom selection of immigrants.

This identification strategy introduces two relevant assumptions about the structure of the DAG. Indeed, we are imposing that there are no indirect paths linking REC to the observable variables included in the vector X or to the unobservable confounding factors (A, NRS). Nevertheless, it can be argued, for example, that the higher the worker's ability is, the higher the probability of having a recognised degree. To overcome these shortcomings, in the second panel of Figure 3, a different identification strategy is proposed. As shown by the DAG, in this latter case, we select the sample by removing from the analysis all the workers with unrecognised degrees, comparing those with tertiary and upper-secondary education. This strategy is allowed because, as shown in Figure 3, those workers with an unrecognised degree show no significant returns to education. This identification strategy shows a main advantage since we can use a back-door criterion to identify ATE. However, sample selection may produce erroneous standard errors, and hence, to obviate this further shortcoming, instead of using a restricted sample, we use the interaction between the education degree and the recognition of that degree (from now on, interacted sample). This identification is still coherent with the DAG presented in the right panel of Figure 3. In this case, the Average Treatment effect (ATE) reads:

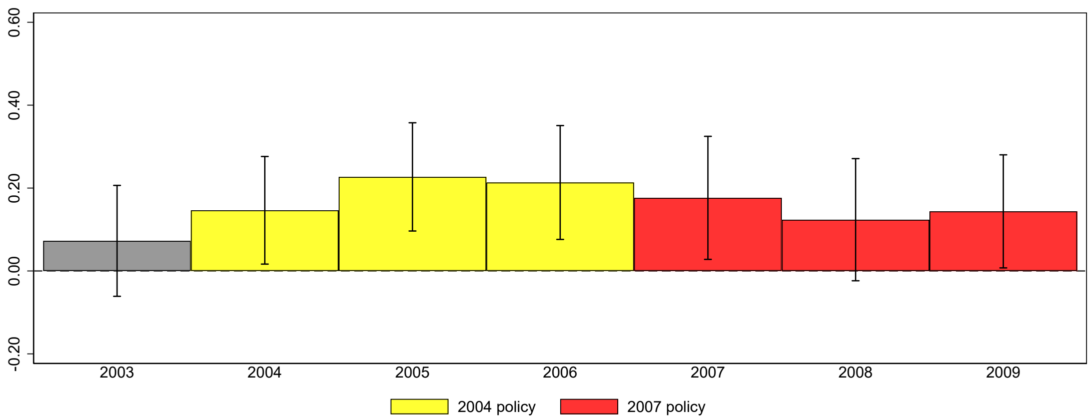
$$\begin{aligned} ATE = & \{E\left[W|ED=1, REC=1\right] - E\left[W|ED=0, REC=1\right]\} \\ & + \{E\left[W|ED=1, REC=0\right] - E\left[W|ED=0, REC=0\right]\} \end{aligned} \tag{2}$$

which converges to the ATE of the restricted sample if there is no difference in the potential outcomes of the workers with unrecognised postsecondary and tertiary education degrees. In other words, we state that the potential outcomes of the workers with unrecognised degrees are exchangeable with respect to the education degree (i.e., $E\left[W|ED=1, REC=0\right] = E\left[W|ED=0, REC=0\right]$).

However, whether we use the restricted or the interacted sample, as shown by the DAG, conditioning on the observable confounders is not enough to identify the ATE, since we have two unobservable confounding factors (A, NRS). These unobservable confounders will be accounted for by using an instrumental variable approach (IV). Indeed, as shown in the DAG, by introducing one or more instruments in the vector Z, we block the indirect paths linking A or NRS to W.

As instruments, we introduce two dummy variables accounting for the enlargement of the European Union to Eastern countries. Two different waves of the enlargement policy can be used: i) the 2004 enlargement policy, involving Cyprus, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, the Slovak Republic and Slovenia, and ii) the 2007 enlargement policy, involving Romania and Bulgaria. The underlying intuition behind the use of these instruments is that the enlargement of EU policies has favoured the transferability of human capital, increasing the probability of a formal recognition of the degree. Indeed, by the treaty of Lisbon (1997), when a country becomes a member of the European Union, the probability of having a legal recognition of the education title increases significantly. In this respect, the policy increases the probability of attracting highly educated migrants by enhancing their possibility of using their human capital in the host country. This hypothesis is illustrated in Figure 4 Panel (a), where we report the probability of having a legally recognised high education ti-

Figure 4: Probability of having a formally recognised high education degree by cohort of immigration



*Notes:*The marginal probabilities are estimated using high education as an outcome variable and interacting the formal recognition of the degree and the immigration cohort. The regression includes the entire set of covariates reported in Tables A1 and A2. Clustered robust standard errors are used to obtain 5% confidence intervals.

tle by the year of immigration. As shown by the graph, after the 2004 EU enlargement, we have a significant increase in the probability of attracting migrants with a recognised tertiary education degree. A similar result also is found when the second policy is accounted for.

An IV identification strategy also is applied when the IT-SILC survey is used to analyse the wage returns to education of the natives. In this case, the identification strategy is in line with the contributions of Brandolini and Cipollone (2002) and Brunello et al. (2000). First, in line with Brandolini and Cipollone (2002), we adopt an IV approach that exploits the exogenous variation in school achievement induced by the 1962 mandatory middle school reform.[16] As shown by the authors, the 1962 reform increased the average years of schooling and school attendance rates, with a persistent positive effect on wages for the cohorts directly affected by the reform. The instrument is then defined as a dummy variable equal to 1 for individuals born from 1962 onwards, and to 0 otherwise. A second instrument exploits the exogenous variation induced by another important reform in the Italian context, introduced by Law 910 of December 1969. This reform extended the possibility of enrolment in college to individuals with completed secondary education, independent of the track (general or vocational) chosen in secondary school. Since the expected age of completion of secondary school is in general 18-19 years, this opportunity was mainly open to cohorts born from 1951 onwards. In line with Brunello et al. (2000), we capture this reform with a dummy equal to 1 for individuals born from 1951 onwards, and to 0 otherwise.

4 Results

Table 1 reports the estimation results for the immigrants. In line with the proposed identification strategy, we first report the OLS estimates and the SURE estimates by applying a

[16]Actually, Heckman et al. (2006) argues that ability differences between individuals begin to open up at early ages for both cognitive and noncognitive skills. This means that a vast array of abilities that influence wages during adults' life cycles are produced by the environment, investment and genes at early stages of childhood. In particular, the returns on early educational investment are higher than returns on late educational investment during child development because of dynamic complementary, self-productivity and multiplier effects in the technology of skill formation (Cunha and Heckman, 2007).

front-door criterion. Then, we move to the estimates that use the interaction between the high education degree and the formal recognition of the education degree. In this latter case, we report OLS and IV estimation results and introduce the two instruments described in the previous section, or rather the dummy variable characterising the 2004 and 2007 EU enlargement policies. It is important to remark that since the IV uses as a core variable the interaction between high education and formal recognition, the two instruments are still interacted with respect to formal recognition.[17]

The first remarkable result is presented in the second column of the Table, where the front-door criterion is applied and the parameter is estimated through the SURE model, described in equation 1. In this case, we introduce only education to account for all the observable and unobservable confounders. Using this identification strategy, we find an educational premium of approximately 19.4%. This elasticity is found to be greater in magnitude than the one estimated through the OLS in the interacted sample (as shown in Column 3) and virtually identical to the ones estimated through IV (Columns 4, 5 and 6 of Table 1).[18] Furthermore, the comparison between the results obtained using a SURE or the IV identification strategy reveals that the absence of a formal recognition of the education degree does not produce a significant education premium. Indeed, whereas in the first case (i.e., applying a SURE model), we also include in the treated group those workers with an unrecognised tertiary education degree, in the IV estimates, those workers are included in the control group. In other words, this finding seems to confirm that the potential outcomes of the workers with unrecognised titles are exchangeable with respect to that title (i.e., $E\left[W|ED=1, REC=0\right] = E\left[W|ED=0, REC=0\right]$).

Table 1: High education on hourly wages, immigrants

	OLS	SURE	OLS interacted *legal qualification*	IV interacted *legal qualification*		
Instruments:				**2004 EU policy**	**2007 EU policy**	**EU policies**
High education	0.008	0.194	0.129	0.202	0.184	0.194
	(0.022)	(0.027)	(0.045)	(0.084)	(0.087)	(0.085)
	[0.711]	[0.000]	[0.004]	[0.017]	[0.035]	[0.023]
Number of observations	2,350	2,369	2,350	2,350	2,350	2,350
R^2	0.357		0.360			
Kleibergen-Paap Wald statistic				60.902	59.655	48.093⋆⋆
Kleibergen-Paap LM statistic				14.937	14.711	15.119
						[0.002]
Hansen J statistic						2.951
						0.229

Notes: Standard errors of the SURE model are estimated through the delta method. Columns 4-6 report, in brackets, double clustered standard errors at the household level and at age at arrival. Following the diagnostic approach implemented in (Yogo, 2004), we use p values for the null hypotheses that the bias in the point estimates on the endogenous variable is greater than 10 percent of the OLS bias, or that the actual size of the t test that the point estimates on the endogenous variable equals zero at the 5 percent significance level. In this respect, the statistics show a joint rejection of the null for a 10% maximal IV size and of 5% maximal IV relative bias (⋆⋆).

Finally, following Bazzi and Clemens (2013), we test the robustness of our IV specification

[17] Actually, Wooldridge (2010) shows that the interaction between an instrument and an exogenous variable provides a new instrument that is still valid. Furthermore, also if we formally are introducing two excluded instruments in the first two IV specifications, the model is still just-identified. As a matter of that, the underidentification test statistic test becomes a further test of a weak instrument, and the Hansen J statistic is reported.

[18] All the instruments used show a high cross-section and time-series variation. When the enlargement policies are analysed, the between standard deviation is approximately 16% and 17%, whereas the within standard deviation is approximately 5% and 13%, respectively.

strategy and report, at the bottom of the table, a weak instrument test statistic (Kleibergen-Paap Wald statistic Kleibergen and Paap 2006), an underidentification test statistic (Kleibergen-Paap LM statistic Kleibergen and Paap 2006) and an overidentification test statistic (Hansen J test Hansen 1982).[19] All the reported test statistics confirm the goodness of fit of the excluded instruments. We remark that in the case of the just-identified IV (i.e., in Columns 4 and 5), the underidentification test statistic must be interpreted as a further test for weak instruments. In this case, the excluded instrument is not weak if the Kleibergen-Paap LM and Wald test statistics are greater than 10.

Table 2: High education on hourly wages, natives

	OLS	IV		
Instruments:		**1962 policy change**	**1969 policy change**	**1969 & 1962 policy changes**
High education	0.130	0.654	0.506	0.511
	(0.012)	(0.442)	(0.119)	(0.118)
	[0.000]	[0.139]	[0.000]	[0.000]
Number of observations	7,662	7,662	7,662	7,662
R^2	0.439			
Kleibergen-Paap Wald statistic		5.905	68.988	34.978⋆⋆
Kleibergen-Paap LM statistic		5.534	63.727	64.179
				[0.000]
Hansen J statistic				0.122
				[0.727]

Notes: In all the columns, we report, in brackets, clustered standard errors at the household level. Following the diagnostic approach implemented in (Yogo, 2004), we use p values for the null hypotheses that the bias in the point estimates on the endogenous variable is greater than 10 percent of the OLS bias, or that the actual size of the t test that the point estimates on the endogenous variable equals zero at the 5 percent significance level. In this respect, the statistics show a joint rejection of the null for a 10% maximal IV size and of 5% maximal IV relative bias (⋆⋆).

In line with the identification strategy proposed in the previous section, we proceed with the analysis by estimating the wage premia of the natives. The results, displayed in Table 2, include OLS and IV estimates. In line with the previous table, when the IV approach is used, we consider, first, the two excluded instruments separately (see Columns 2 and 3) and then together to introduce an overidentification test statistic.[20] In this respect, the check reveals that the 1962 mandatory middle school reform is a weak instrument (as shown by the Kleibergen-Paap Wald statistic and by the Kleibergen-Paap LM statistic) and exaggerates the wage returns of the natives. In contrast, when we introduce the dummy variable accounting for the 1969 reform or when we consider all the instruments together, we see that all the reported test statistics confirm the goodness of the instrument set used. That is, from the last column of the table, we find an education premium in the Italian population of approximately 51%.

The comparison between these results and those estimated for the immigrant population reveals that there is a significant gap in the educational wage premia of the two groups, with natives gaining more than 30 percentage points with respect to immigrants. However, this gap in hourly wages may be interpreted by the mismatch in the labour market and hence the overeducation of the immigrant workforce, or rather by the differences in the quality and comparability of the acquired human capital within the host labour market. Indeed, as shown

[19] Also, if we formally introduce, in Columns 4 and 5, two excluded instruments, we cannot use them to perform the overidentification test statistic, since they are obtained by a linear combination of the relevant excluded instrument. Hence, in this case, we still use a just-identified IV.

[20] Introducing each instrument in a separate regression is informative since it allows us to interpret the IV as a Wald estimator and to inspect if and in what respect the estimated parameter varies in each estimate (Angrist and Pischke, 2008).

Table 3: High education on hourly wages, immigrants from countries with a GDP higher than the sample median

	SURE	IV interacted *legal qualification*		
Instruments:		**2004 EU policy**	**2007 EU policy**	**EU policies**
High education	0.349	0.332	0.311	0.320
	(0.040)	(0.077)	(0.083)	(0.077)
	[0.000]	[0.000]	[0.000]	[0.000]
Number of observations	1,251	1242	1242	1242
Kleibergen-Paap Wald statistic		388.049	44.201	286.025⋆⋆
Kleibergen-Paap LM statistic		11.696	11.999	12.450
				[0.006]
Hansen J statistic				2.165
				[0.339]

Notes: Standard errors of the SURE model are estimated through the delta method. Columns 2-4 report, in brackets, double clustered standard errors at the household level and at age at arrival. Following the diagnostic approach implemented in (Yogo, 2004), we use p values for the null hypotheses that the bias in the point estimates on the endogenous variable is greater than 10 percent of the OLS bias, or that the actual size of the t test that the point estimates on the endogenous variable equals zero at the 5 percent significance level. In this respect, the statistics show a joint rejection of the null for a 10% maximal IV size and of 5% maximal IV relative bias (⋆⋆).

by Friedberg (2000) in the latter case, the level of economic development of origin countries positively affects the transferability of studies completed abroad. Hence, in Table 3, we replicate the estimation results proposed in Table 1 by considering only origin countries with a GDP level higher than the sample median.[21] As shown by the table, removing from the analysis immigrants coming from countries with a GDP lower than the sample median increases the educational wage premium, which in this case is approximately 33%. Nevertheless, in this case, we also find a significant difference between natives and immigrants, with a corresponding wage gap of approximately 18 percentage points. This result is still amplified by the fact that we are controlling for the overeducation that could be caused by the lack of formal recognition of the education degree.

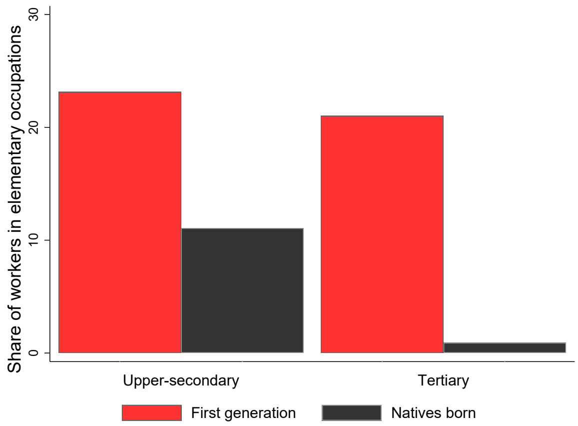
To give more emphasis to this latter result, in Figure 5, we report the share of workers employed in elementary occupations while comparing immigrants and natives. As shown by the graph, highly educated immigrants are overrepresented in elementary occupations (approximately 20%) with respect to natives (less than 1%). This finding is consistent with Chiswick and Miller (2009), who found that overeducation disproportionally affects immigrants rather than natives.

4.1 Robustness checks

As shown by the two DAGs reported in Figure 3, the identification of the high-education returns for immigrants crucially depends on the assumptions that we have proposed to isolate the mediating effect of the formal recognition of the education degree. This statement is valid both when the SURE model and the IV framework are applied. Given the relevance of these assumptions, in this section, we propose two robustness checks to show the reliability of

[21]The considered countries are Algeria, Argentina, Austria, Belgium, Brazil, Bulgaria, Czech Republic, Chile, Cyprus, Colombia, Denmark, Ecuador, Estonia, Finland, France, Germany, Japan, Greece, Iran, Ireland, Libya, Lithuania, Luxembourg, Mauritius, Mexico, Norway, Holland, Panama, Portugal, UK, Romania, Russian Federation, Seychelles, Slovenia, Spain, US, South Africa, Suriname, Sweden, Switzerland, Thailand, Turkey, Ukraine, Uruguay, and Venezuela.

Figure 5: Share of immigrant and native workers employed in elementary occupations



our identifications. That is, in Table 4, we replicate the main estimates for the immigrants by comparing workers with a formal recognition with those who have never applied for such recognition. In this case, hence, we remove from the analysis all the workers who have applied for a formal recognition but have not received it or are still waiting to receive it. By this check, we want to see if and to what extent the previous results are robust if we consider two groups (i.e., the treatment and control groups) that are more distant with respect to their characteristics. For example, we can imagine that the higher the unobservable abilities of the worker are, the higher the probability that that worker will apply for a degree recognition.

Table 4: Placebo test, unbalancing the treated and control groups

	OLS	SURE	OLS interacted *legal qualification*	IV interacted *legal qualification*		
Instruments:				**2004 EU policy**	**2007 EU policy**	**EU policies**
High education	0.008	0.212	0.103	0.177	0.159	0.170
	(0.022)	(0.029)	(0.046)	(0.081)	(0.085)	(0.082)
	[0.711]	[0.000]	[0.025]	[0.029]	[0.062]	[0.039]
Number of observations	2,350	1,898	1,883	1,883	1,883	1,883
R^2	0.357	0.399				
Kleibergen-Paap Wald statistic				56.170	51.506	41.216
Kleibergen-Paap LM statistic				14.473	14.542	14.910
						[0.002]
Hansen J statistic						2.383
						0.304

Notes: Standard errors of the SURE model are estimated through the delta method. Columns 4-6 report, in brackets, double clustered standard errors at the household level and at age at arrival. Following the diagnostic approach implemented in (Yogo, 2004), we use p values for the null hypotheses that the bias in the point estimates on the endogenous variable is greater than 10 percent of the OLS bias, or that the actual size of the t test that the point estimates on the endogenous variable equals zero at the 5 percent significance level. In this respect, the statistics show a joint rejection of the null for a 10% maximal IV size and of 5% maximal IV relative bias (⋆⋆).

As shown in Table 4, only slight differences are found in the estimated parameters with respect to the ones reported in Table 1. This finding confirms the validity of the proposed identification strategy.

As a second robustness check, we propose a placebo test aimed at showing that *REC* is effectively a mediating variable in the causal relationship between education and hourly wages. In this respect, the placebo is performed by changing the content of the mediating variable and comparing those workers who have never applied for a formal recognition of the education degree with those who have not received such recognition. If the proposed identification is robust, we expect to find no significant results.

Table 5: Placebo test, using only workers with an unrecognised title

	OLS	SURE	OLS interacted *legal qualification*	IV interacted *legal qualification*		
Instruments:				**2004 EU policy**	**2007 EU policy**	**EU policies**
High education	0.008	0.045	0.024	0.032	0.042	0.041
	(0.022)	(0.022)	(0.042)	(0.068)	(0.064)	(0.064)
	[0.711]	[0.041]	[0.561]	[0.636]	[0.518]	[0.522]
Number of observations	2350	1,985	1968	1968	1968	1968
R^2	0.357	0.329				
Kleibergen-Paap Wald statistic				37.345	38.791	29.272
Kleibergen-Paap LM statistic				11.850	11.881	11.921
						0.008
Hansen J statistic						0.218
						0.897

Notes: Standard errors of the SURE model are estimated through the delta method. Columns 4-6 report, in brackets, double clustered standard errors at the household level and at age at arrival. Following the diagnostic approach implemented in (Yogo, 2004), we use p values for the null hypotheses that the bias in the point estimates on the endogenous variable is greater than 10 percent of the OLS bias, or that the actual size of the t test that the point estimates on the endogenous variable equals zero at the 5 percent significance level. In this respect, the statistics show a joint rejection of the null for a 10% maximal IV size and of 5% maximal IV relative bias (⋆⋆).

As shown in Table 5, the test failed to reject this hypothesis only when the SURE model was applied. However, this result does not imply that the front-door criterion is less robust than the IV. Indeed, in this case, while estimating the SURE model, we find that education is no longer significant when regressed on REC (see equation 1), and hence, education is no longer controlling for the observable and unobservable confounding factors. That is, the significant effect depends on the indirect paths linking education to hourly wages though the observable and unobservable variables (see Figure 3) since the formal recognition of the education degree is no longer a mediating variable in this relationship.

5 Conclusions

This paper examines whether the returns to human capital differ for natives and immigrants and whether they depend on the formal recognition of the education degree. We contribute to the literature in some respects. First, we show that an immigrant with a tertiary education has a 20% increase in hourly wages when compared to workers with a postsecondary education. This result is valid only when we account for highly educated workers with a formal recognition of the education degree. Indeed, the absence of such recognition does not produce any return to education. Second, we find a wage gap of approximately 31 pp between immigrants and natives. When we isolate only migrants coming from those countries with a GDP higher than the sample median, to reduce the differences in the quality and comparability of the acquired human capital within the host labour market, the education premium of the immigrant workforce increases (approximately 33%), but remains significantly different with respect to that of the natives.

These results shed new light on the two channels that may contribute to the wage gap between highly educated immigrants and natives in Italy. The first channel moves behind the heterogeneity of highly educated immigrants with respect to their education quality and comparability and on relevant differences in the formal process of recognition of the education degree, which is found to be heterogeneous with respect to the level of development of the origin country. The second channel is, hence, linked to job mismatch and the overeducation of the immigrant workforce. This second effect could be fostered by the extensive use, in Italy, of mass regularisations aimed at legalising migrant workers who had acceded to the market without authorisation. Hence, policies aimed at changing the recruitment process may have a prominent effect in increasing the attractiveness of the country with respect to the foreign qualified labour force and reducing the wage gap between qualified immigrants and natives. Furthermore, the implementation of instruments envisaging well-designed processes of formal recognition also may contribute to enabling a more careful recruitment of human resources and a better capitalisation of migrants' human capital.

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Appendix A. Descriptive statistics

Table A1: Common covariates

		ILCHF2009	ITSILC2009
Gross hourly wage (log)		2.05 (0.38)	2.47 (0.40)
Experience in the labour market		18.92 (9.44)	22.78 (10.76)
Gender			
	Male	2556 (55.6%)	6599 (56.3%)
	Female	2041 (44.4%)	5121 (43.7%)
Age class			
	15-29	900 (19.6%)	1343 (11.5%)
	30-39	1697 (36.9%)	3184 (27.2%)
	40-49	1353 (29.4%)	3985 (34.0%)
	50-59	579 (12.6%)	2914 (24.9%)
	60-64	68 (1.5%)	294 (2.5%)
Education degree			
	No or primary	786 (17.1%)	547 (4.7%)
	Lower-secondary	1442 (31.4%)	3278 (28.0%)
	Upper-secondary	1959 (42.6%)	5965 (50.9%)
	Tertiary	410 (8.9%)	1930 (16.5%)
Years after education			
	<5	162 (3.8%)	1077 (9.2%)
	5-14	1151 (26.9%)	2290 (19.6%)
	15-24	1620 (37.8%)	2952 (25.3%)
	>25	1349 (31.5%)	5,363 (46,0%)
Vocational course			
	Yes	280 (6.5%)	2500 (21.4%)
Health condition			
	Not good	694 (15.2%)	2252 (19.4%)
	Good	3865 (84.8%)	9339 (80.6%)
Family link			
	Head	3421 (74.4%)	5965 (50.9%)
	Spouse	630 (13.7%)	3240 (27.6%)
	Parents	37 (0.8%)	23 (0.2%)
	Sons and sons spouse	204 (4.4%)	2334 (19.9%)
	Others	305 (6.6%)	158 (1.3%)
Marital status			
	Single	1517 (33.0%)	3645 (31.1%)
	Married	2894 (63.0%)	7239 (61.8%)
	Divorced/Widowed	186 (4.0%)	836 (7.1%)
Family size (members)			
	One	571 (12.4%)	2134 (18.2%)
	Two	833 (18.1%)	5264 (44.9%)
	Three	1033 (22.5%)	2016 (17.2%)
	Four	856 (18.6%)	1021 (8.7%)
	Five or more	1304 (28.4%)	1285 (11.0%)
Region of residence			
	North-west	1042 (22.7%)	2850 (24.3%)
	North-east	1149 (25.0%)	3023 (25.8%)
	Centre	921 (20.0%)	2812 (24.0%)
	South	782 (17.0%)	2144 (18.3%)
	Islands	703 (15.3%)	891 (7.6%)
Contract type			
	Permanent	3233 (70.3%)	10497 (89.6%)
	Temporary	913 (19.9%)	1051 (9.0%)
	No contract	451 (9.8%)	172 (1.5%)
Contract duration			
	Full-time	3861 (84.0%)	10373 (88.5%)
	Part-time	736 (16.0%)	1347 (11.5%)
Sector			
	Private	4484 (97.5%)	8213 (70.1%)
	Public	113 (2.5%)	3507 (29.9%)
Firm size			
	Small	3008 (65.4%)	4019 (34.8%)
	Medium	995 (21.6%)	3464 (30.0%)
	Big	594 (12.9%)	4053 (35.1%)

Table A2: Immigrants' specific covariates

	ILCHF2009
	First generation (N = 4,597)
Experience abroad	11.72 [6.54]
Year of immigration	
1979-1983	32 (0.7%)
1984-1988	49 (1.1%)
1990-1994	538 (11.7%)
1995-1999	772 (16.8%)
2000-2004	1786 (38.9%)
2005-2009	1420 (30.9%)
Linguistic proximity	
Yes	649 (14.1%)
No	3948 (85.9%)
Motivation to emigrate	
To work	3803 (82.7%)
Family	605 (13.2%)
Other	189 (4.1%)
Do you want to leave Italy?	
No	3254 (70.8%)
Yes	1343 (29.2%)
Recognition of qualifications	
Recognised	1,140 (13.6%)
Waiting to be recognised	107 (1.3%)
Never applied	5,634 (67.4%)
Not recognised	1,482 (17.7%)