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The Overeducation of Immigrants in Europe

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The Overeducation of Immigrants in Europe

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Abstract

This paper explores the overeducation of tertiary-educated migrants in European labour markets. Using data from the European Labour Force Survey (2012–2022), we show that immigrants, particularly those from non-EU countries, are significantly more likely to be overeducated than natives. Despite a general decline in overeducation levels for all groups over time, the immigrant-native gap remains, especially for foreign-educated migrants. Furthermore, the likelihood of overeducation for foreign-educated migrants increases until 15–19 years after migration, a pattern consistent across all areas of origin and migration cohorts. Importantly, differences in educational quality between origin and destination countries do not primarily account for these overeducation differentials. The findings underscore the need for policies that better align immigrants' skills with labour market demands in Europe to avoid the waste of valuable immigrants' skills, which are harmful not only to migrants but to the economies of receiving countries too.

JEL Codes: J15, J61, F22
Keywords: Skill mismatch; EU labour markets; immigration.

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1 Introduction

Immigrants represent a sizeable and growing share of the total European labour force. In many contexts, they also represent a valuable injection of labour supply in a setting characterised by an ageing population and widespread skill shortages (EURES, 2024). In fact, in many European labour markets, particularly in skilled professions, employers struggle to find or retain suitably qualified candidates, prompting consideration of immigration as a potential solution to alleviate these shortages, at least in the short run.[1] Yet, immigrants are disproportionately employed in low-pay occupations relative to natives, even though approximately one-third of immigrants currently residing in Europe are highly educated. In fact, tertiary education is nearly as common among immigrants as it is among EU natives, a fact often overlooked in the public discourse on immigration.

This paper analyses how well immigrants are matched to jobs in European labour markets. Specifically, we aim to assess to what extent they are employed in occupations that match their educational qualifications and skills credentials or to what extent they are overqualified for the occupations they perform.

These questions are of paramount policy importance because a good skills-job match is in the interest of migrants and the host country's economy at large. It is increasingly common in policy circles to discuss ways of attracting and retaining foreign workers with in-demand skills and experience. For example, the New Pact on Migration and Asylum, approved by the European Parliament in April 2024, envisages the launch of Talent Partnerships between the EU and third countries. These partnerships aim to provide a comprehensive policy framework to boost mutually beneficial international mobility based on better matching of labour market needs and skills between the EU and partner countries. While mobility schemes of this type

[1] See, for instance, the press release advertising the EC action plan to tackle labour shortages: https://commission.europa.eu/news/tackling-labour-and-skills-shortages-eu-2024-03-20_en, last accessed on 30/09/2024.

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have the potential to prove beneficial for both origin and sending countries, another critical question is how to productively use the skills of migrants who are already in the EU countries and who "have brought with them" the human capital they acquired in their home countries (Friedberg, 2000). If such human capital is only imperfectly transferable between countries (Hendricks & Schoellman, 2017) due, e.g., to language barriers (Chiswick & Miller, 2009) or lack of formal recognition of foreign qualifications (Brücker et al., 2021, Anger et al., 2022), then migrants may end up in jobs they would be – in principle, at least – over-qualified for. Such over-qualification would entail a "waste" of the home country's human capital that could be appropriately used if suitable re-skilling policies were implemented.

The pervasive overeducation of immigrants across European countries was first noted in a JRC report by Biagi et al., 2010. This paper builds on that study and – while confirming their main results – extends the analysis in several ways. First, we consider a longer time span, analysing data until 2002 (the latest year for which data are currently available), whereas their earlier contribution ended in 2016. Second, we adopt a tighter definition of overeducation, comparing workers' education within more detailed occupation cells (three rather than two-digit ISCO occupations) and also within a calendar year and age group. Third, we analyse in detail the evolution of overeducation differentials over the whole decade we study, rather than providing pooled estimates for the whole period. Fourth, we provide separate estimates for EU and non-EU migrants and for home- and foreign-educated migrants. Fifth, we study in detail how the immigrant-native overeducation differentials evolve with time spent in the host country, rather than simply differentiating between "recent" and "long-term" migrants.

The paper is structured as follows: in the next section, we discuss the concept of overeducation and its measurement. Then, in section 3, we present the data used for the analysis and in section 4, we describe the key characteristics of our sample. Section 5 shows

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the degree of overeducation of immigrants and natives in Europe, how it has evolved, the differences between domestically- and foreign-educated migrants, and how the immigrant-native overeducation differentials change with years since migration. Finally, in section 6, we assess the role of educational quality in explaining the measured overeducation. Section 7 concludes and suggests avenues for future research.

2 Overeducation

2.1 Definition and consequences

Overeducation is the situation in which an individual has completed more education than her current job requires. It represents a suboptimal education–job match, which often – though not always – overlaps with overskilling, i.e. the situation in which an individual is unable to fully use acquired skills and abilities in her current job (see Sloane and Mavromaras (2020) for an overview and Chevalier (2003) for a thorough discussion of the difficulties in the definition and measurement of overeducation).

In his extensive review of the literature on overeducation, McGuinness (2006) concluded that the consequences of overeducation are likely to be non-trivial in real terms in the economy: potentially costly to both workers and firms, as well as affecting, on a macro-level, economic growth. Overeducation may impact wage levels and workers' jobs and career mobility. An early contribution by Sicherman (1991) showed that workers who are employed in occupations requiring less schooling than they possess receive higher wages than their coworkers (holding other characteristics constant) but lower wages than workers with similar levels of schooling who work in jobs in which their education perfectly equals what is required. Similar results were also reached by other, more recent studies (e.g. Rubb, 2003, Cohn and Ng, 2000). In general, most studies show that overeducated workers tend to have lower

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earnings than comparable well-matched individuals, but also that overeducation tends to decrease for the same workers over time (e.g. Dolton and Vignoles, 2000, Frenette, 2004, Carroll and Tani, 2013)

Educational mismatches also have important implications on occupational mobility, other than in earnings. In particular, the theory of career mobility (Sicherman & Galor, 1990) suggests that current wage penalties for overeducated workers are compensated by better promotion prospects, which would lead to higher earnings growth for overeducated worker (Sicherman, 1991). On the other hand, since overeducated workers are usually more transient than their well-matched or undereducated counterparts, employers' incentives to invest in their human capital are smaller, leading to lower returns to labour market experience. Additionally, the unused human capital of overeducated workers might progressively depreciate, implying a lower rate of returns over time. Empirical studies provide mixed evidence in this regard (e.g. Robst, 1995, Büchel and Mertens, 2004, Dinerstein et al., 2022)

2.2 Measurement of "overeducation"

When attempting to measure overeducation, the main issue is choosing the criteria against which to assess the true "required" level of schooling for a job. Three alternative methodologies, reflecting different conceptual frameworks, exist.

The first method relies on self-assessment of overeducation conditions. Workers are directly asked for information about the schooling requirements for their jobs and their perception of mismatch with respect to the educational requirements. This method allows for heterogeneous education requirements within the same occupation. However, the empirical evidence suggests that self-assessed mismatch is often influenced by other job features, such as occupational status and particularly income (Dolton & Vignoles, 2000). Individuals who participate in the survey may be inclined to exaggerate the educational requirements of their

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job for different reasons (Borghans & Grip, 2000), and self-assessed overeducation might also be particularly gender biased (Leuven & Oosterbeek, 2011).

A second method exploits the information included in job descriptions and infers the official educational requirements accordingly. Each occupation is analysed by a professional job analyst or through categorisation tools (e.g., text analysis) to provide an exogenous measure of the required education in each detailed occupation. However, such evaluations and detailed categorisation are available for a limited number of countries (and not generalisable across countries, as different occupations may require different types of knowledge across them) and are updated infrequently.

The third method relies only on the actual observed "realized matches" in the labour market. According to this method, workers are considered overeducated if their educational attainment is higher than the mean (Verdugo and Verdugo, 1989) or modal (Kiker et al., 1997) level of education of other workers in the same occupation. This method poses at least two measurement challenges. First, standards in educational requirements change over time. Some papers (Jacobs et al., 2021) highlighted how this approach does not account for cohort effects in education attainment, i.e., the fact that levels of education have substantially increased over time and that the education credentials of older workers cannot be directly compared with those of their younger coworkers. Furthermore, the education requirements for a given occupation will likely vary across professions over the years. A way to deal with this issue is to compare the educational attainment of workers to that of other individuals in the same occupation *and* age group. Second, the choice of the mean or modal occupational education as the central measure against which to compare workers' education is contentious. Both measures have advantages and drawbacks. In general, using the modal educational qualification in an occupation is better when the data do not report information about years of education received but only about educational qualifications. However, the choice of

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the mode as a reference point can potentially have a sensitive impact on the measurement, depending on the specific distribution of educational levels within an occupation group. In particular, the use of the mode in the empirical literature that compares methodologies appeared to give higher values of overeducation with respect to the use of the mean. Hence, in the interpretation of the results, the absolute levels of the incidence of overeducation inferred by this method of measurement must be taken carefully. In contexts where the main interest of the analysis is the differential in overeducation risk between two populations (natives and foreign-born) rather than overeducation *levels*, however, this is only a limited concern. Finally, the statistical method of overeducation measurement implies evaluating a context that is the result of demand and supply forces. This context does not only reflect pure requirements but also ignores variation in required schooling across jobs within a unique occupation.

Some studies have tried to assess whether the use of different measurement techniques leads to different estimates of the consequences of overeducation. For what concerns earnings, some authors claim that the results are pretty independent of the measure of required education used (Chiswick and Miller, 2010; Cohn and Khan, 1995; Kiker et al., 1997). Another stream of the literature has tried instead to validate the different measures. For instance, Verhaest and Omey (2006) compared the realized-match method measure, the job-description measure and two types of self-assessed measures using the same method of evaluation but did not report one of these methods as being superior to the others. According to Hartog (2000), the job-description method is "conceptually superior," but its measurement is often flawed. Therefore, there are no clear guidelines in the literature regarding the appropriate measure of required education.

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2.3 Our approach: *realized-matches* method

In this paper, we will adopt a definition of overeducation based on the *realized-matches* method. Thus, we define "overeducated" individuals whose educational qualification is above the reference values in a given occupational cell. This definition allows us to compute a comparable measure of overeducation for the highest number of countries and the highest number of years, whereas measures based on other approaches are at most available for some countries in some years. In particular, given the categorical nature of the educational qualification variable (which follows the ISCED classification of education, see Section 3), we use the modal educational level in the cell as a reference value of education. Furthermore, to avoid the presence of mismatched immigrants altering the measurement of modal education, we only consider the modal education of native workers. We account for changes in educational requirements across years, countries and birth cohorts by defining cells in terms of 3-digit ISCO occupations by year, country, and age (in ten-year groups).

Formally, we define individual i as overeducated ($OE_i = 1$) if their own education ($ISCED_i$) is above the modal education of natives ($ISCED(mode)_{otca}$) in the same occupation o, year t, country c and age group a.

$$OE_{iotca} = \begin{cases} 1 & \text{if } ISCED_i > ISCED(mode)_{otca} \\ 0 & \text{if } ISCED_i \leq ISCED(mode)_{otca} \end{cases}$$

3 Data

Our analysis is based on data from the European Labour Force Survey (EULFS), a large household sample survey that provides information on labour market participation of individuals aged 15 and over for all EU countries, as well as Iceland, Norway, and Switzerland.

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The EULFS is currently available for all years between 1983 and 2022, with the length of the time series for each individual country depending on when they joined the EU. Data at the European level are made comparable across countries and over time by using consistent concepts and definitions.

The EULFS includes detailed information on individuals' demographics, educational qualifications (classified according to the International Standard Classification of Education, ISCED), employment status and – for those in employment – on occupation (classified by the International Standard Classification of Occupations, ISCO). Also, crucially for this study, it contains migration-related questions such as country of birth (grouped in macro-areas) and years since migration. We use the former variable to identify immigrants: throughout the paper, we define "immigrants" as "foreign-born." However, information on country of birth is available for Germany only since 2017. Thus, for Germany, we define immigrants as foreign-nationals until 2016 and as foreign-born from 2017 onward. We will also often break down the sample into "EU" and "non-EU" immigrants. Since the EULFS does not report detailed country of birth, EU and non-EU status depend on which countries belong or do not belong to the European Union in any given year. This fact leads to some inconsistency over time. Most notably, over the period we consider, the UK left the European Union in 2020. Thus, UK-born individuals living abroad will be classified as "EU" until 2019 and as "non-EU" from 2020 onward. Additionally, Croatian-born immigrants will be coded as non-EU in 2012 and as EU from 2013 onward.

We use information on the year of attainment of the highest level of education (*hatyear*) and on the time spent in the host country (*yearesid*) to distinguish between immigrants who completed their education abroad before moving to their current country of residence (*foreign-educated* immigrants), and those who studied and graduated in the host country (*home-educated* immigrants).

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In this paper, we focus on the decade 2012–2022 (the latest year that is currently available) and consider only countries that are consistently present in the EULFS in all years. We also exclude any country with fewer than 100 immigrant observations in more than one year. As a result, our sample consists of 24 countries: Austria, Belgium, Cyprus, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Spain, Sweden, Switzerland.[2]

We focus on working-age individuals who are old enough to have typically completed their education (25–64 years old) and who have been in the labour market for a maximum of 39 years, measured from when they attained their highest level of education. Since our focus is on overeducation, we only include in the sample individuals who are currently employed and have non-missing information on occupation and educational qualification. Our sample consists of 11,596,117 such individuals. Additionally, since overeducation is a meaningful concept only for highly educated individuals, we will focus most of the analysis on highly educated (ISCED 1997 level 5 or above) immigrants and contrast them with highly educated natives. Our sample includes 4,415,945 highly educated individuals, 3,898,397 natives, and 517,548 immigrants (245,621 from the EU and 251,944 from non-EU countries).

In the analysis on overeducation, we exclude year-country-occupation-age cells with less than 15 natives (the group for which we compute the modal education).

4 Descriptive statistics

In this section, we provide an overview of our sample and describe some key characteristics of the immigrant workforce in Europe.

[2] Note that Slovenia is not included in our sample due to a lack of information on the year of attainment of the highest level of education for 2021 and 2022.

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In Figure 1, the dashed line represents the share of immigrants in the total employed population of the 24 countries in our sample. Instead, we report the same shares in the dotted and solid lines but distinguish between immigrants from non-EU and EU countries, respectively. Foreign-born workers in Europe have steadily increased over the years we consider, rising from 11.8% of total employment in 2012 to 15.5% in 2022. As the graph illustrates, most immigrants originate from outside the European Union. In fact, EU immigrants comprised only about 35% of the total immigrant population in 2022. From 2012 to 2022, the shares of immigrants from both EU and non-EU countries increased, with non-EU immigrants rising from 6.2% to 10.2% and EU immigrants increasing from 3.8% to 5.3%.[3]

Figure 1: Shares of immigrants in total employment in Europe

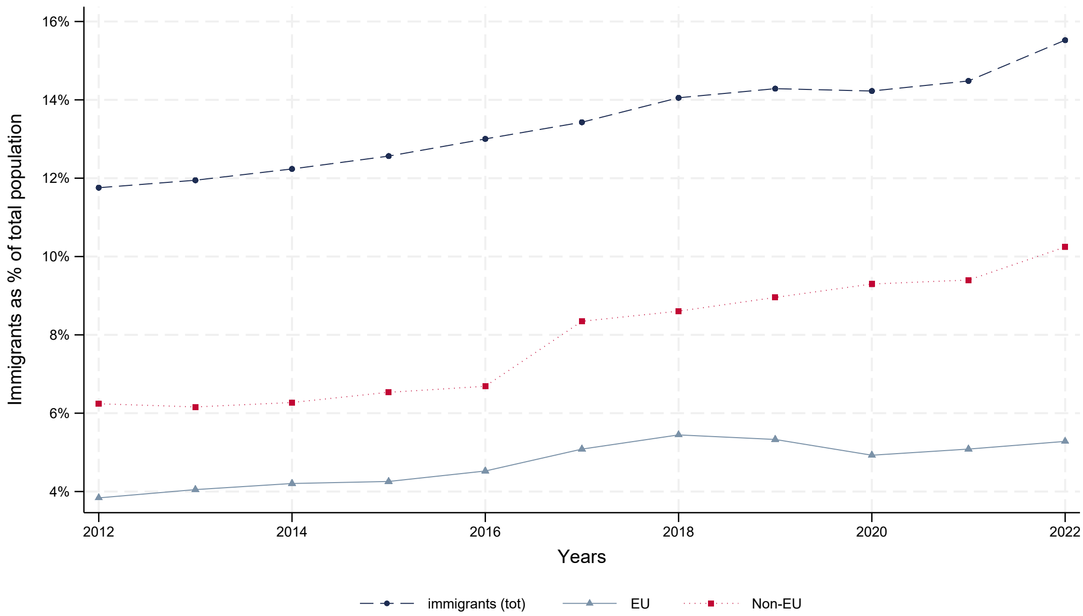

Figure 2 illustrates instead the share of highly educated individuals among employed natives and immigrants over the years. As explained in section 3, we define "highly educated"

[3]Remember that, as explained in Section 3, figures before 2017 and from 2017 onward are not perfectly comparable due to a change in the definition of immigrants in Germany, and that as a result of Brexit, UK immigrants passed from the EU to the non-EU category in 2020.

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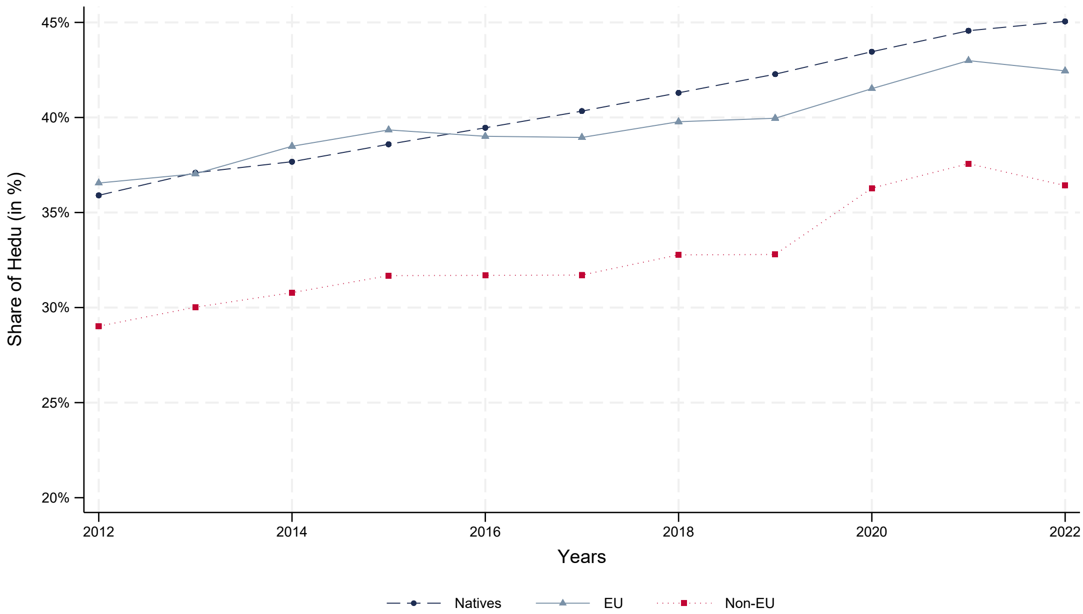
individuals with tertiary education (ISCED level strictly above 4). The graph shows that the share of tertiary increased across all subgroups between 2012 and 2022, reflecting the secular trend of increasing education levels. Immigrants from the European Union have tertiary education levels similar to those of natives, though slightly lower from 2016 onwards. Non-EU immigrants consistently have lower percentages of tertiary-educated individuals than both natives and EU migrants.

Figure 2: Shares of highly educated among employed immigrants and natives



In Figure 3, we plot the share of highly educated immigrants against the share of highly educated natives among the respective populations who are employed, for each country and for our sample as a whole (in red) in 2022. The Figure clearly shows a positive correlation between the two variables: countries with higher shares of tertiary-educated natives also tend to have higher shares of highly educated immigrants. Across the entire sample, 38.5% of immigrants and just over 45% of natives are tertiary educated.

Most countries lie around the 45-degree line. Notable exceptions include Luxembourg, Ireland, Sweden, and Switzerland, which have higher shares of highly educated immigrants compared to natives. Conversely, Greece and Spain have a considerably lower share of highly educated immigrants compared to natives. Italy stands out as the country with the lowest share of highly educated immigrants and, together with Czechia, the lowest share of tertiary educated natives in its workforce. The strength of the correlation between immigrants' and natives' education has increased over time: a linear regression of the share of tertiary educated immigrants on the share of tertiary educated natives delivers an estimated slope coefficient of 0.92 in 2022 (the year displayed in Figure 3). The same regression estimated on 2012 data produces an estimated slope coefficient of 0.7 instead.

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Figure 3: Highly educated immigrants and natives (2022)

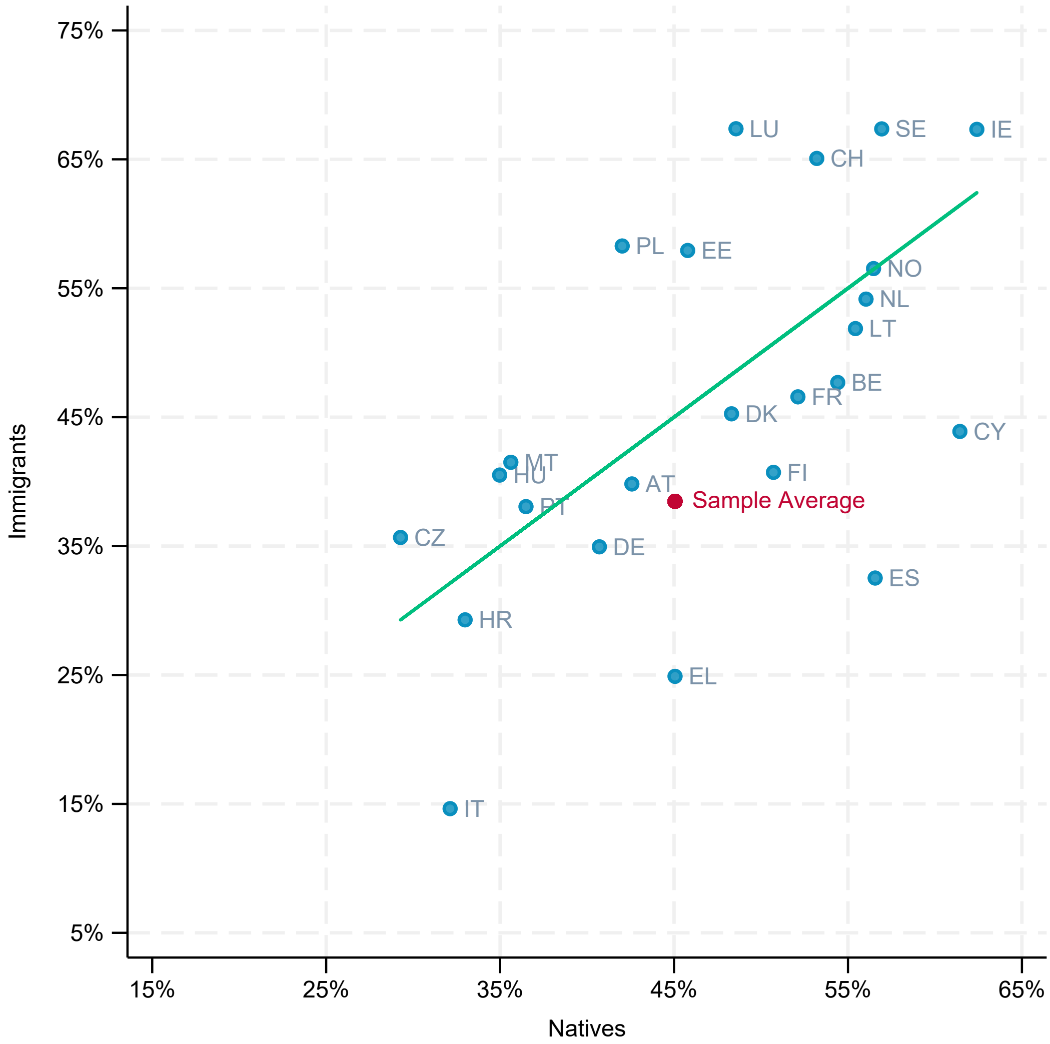

Figure 4 depicts the evolution of the shares of highly educated immigrants in total employment across all countries between 2012 (triangles) and 2022 (squares), whereas in Figure 5 and Figure 6 we break down the immigrant population into, respectively, EU and non-EU origin. The green lines represent increases in the shares of tertiary educated immigrants over time, while the red lines represent decreases. As we have also shown in Figure 2, there is an overall upward movement in the percentage of tertiary-educated individuals across all groups. This graph confirms that this upward movement is consistent across almost all countries, although there is heterogeneity in the magnitude of the increase. The only exceptions are Estonia and Norway.

Figure 4: Shares of highly educated immigrants by country

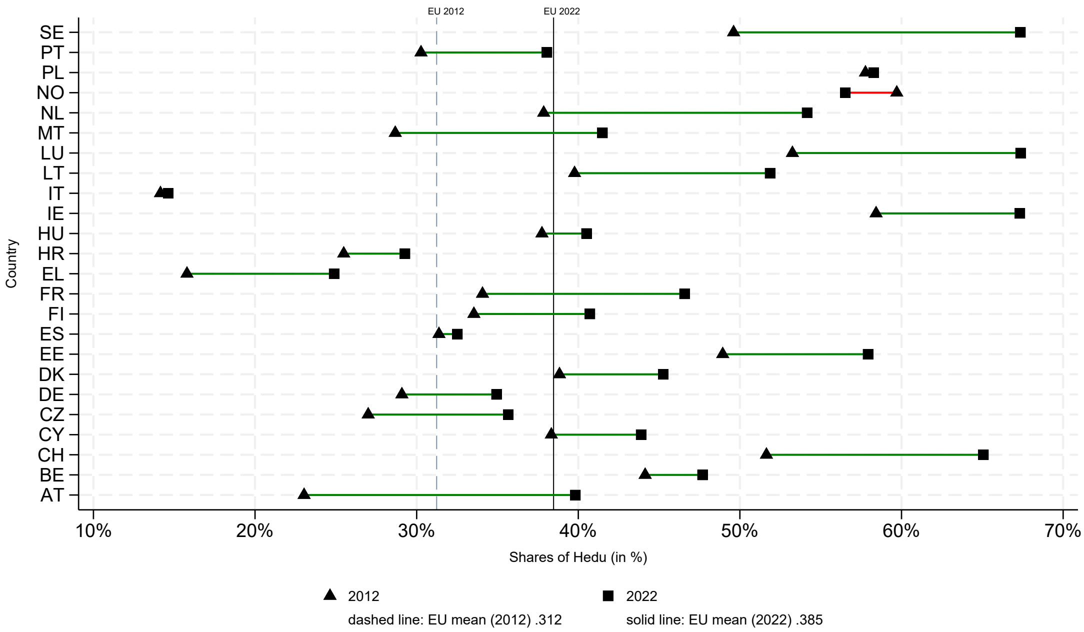

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Figure 5: Shares of highly educated immigrants by country (EU)

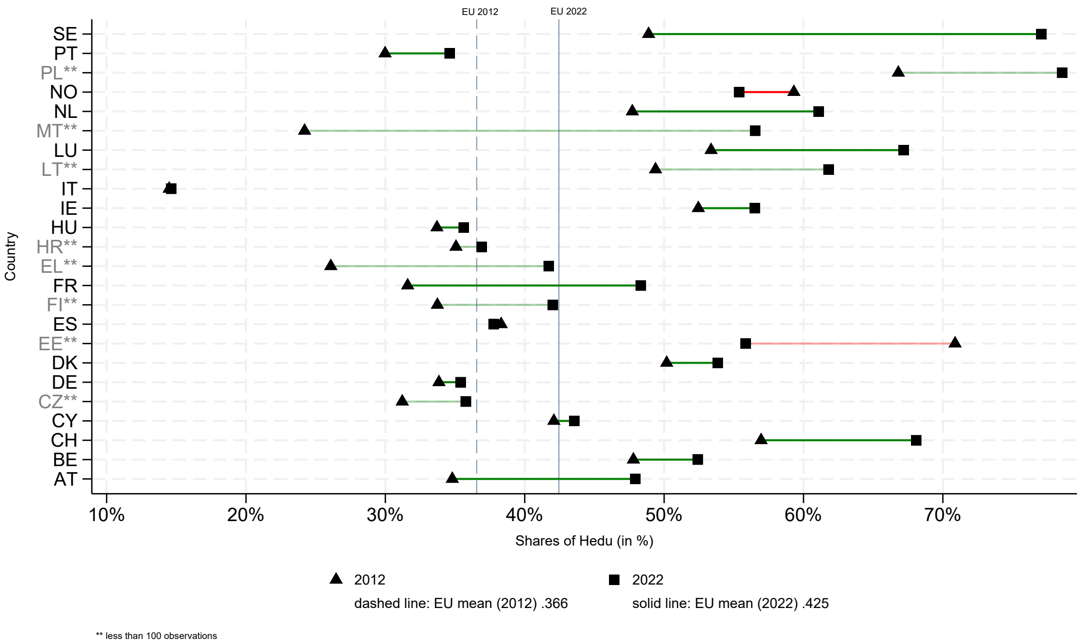
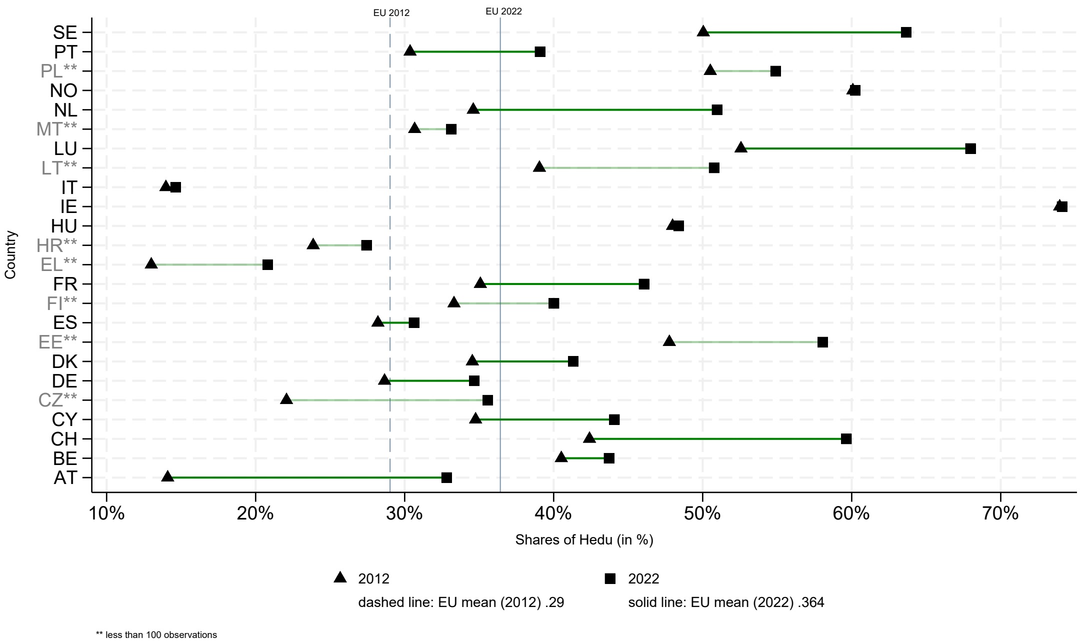


Figure 6: Shares of highly educated immigrants by country (Non-EU)



5 Overeducation

In this Section, we focus on the measurement of the overeducation of highly educated individuals. Thus, our sample now includes only employed individuals with tertiary education (see Section 3 for a description of the sample and Section 2.3 for details on the definition of overeducation).

The left panel of Figure 7 reports the evolution of the proportion of tertiary-educated immigrants and natives that are over-educated according to our definition between 2012 and 2022. The share of overeducated is consistently higher among immigrants than among natives, although it has been declining over time for both groups. In 2012, the percentage of overeducated natives was around 27%, while for immigrants, it was close to 41%. By 2022, these shares were down to 21% for natives and 34% for immigrants. We report the same information in the right panel of Figure 7, breaking down the foreign-born population into EU and non-EU migrants. Both groups exhibit higher levels of overeducation than natives, with non-EU migrants displaying the highest values in all years. Over the years, the decline in overeducation shares has been more pronounced among non-EU immigrants, decreasing by about 9 pp, while the decrease among European immigrants has been more gradual, by about 3 pp.

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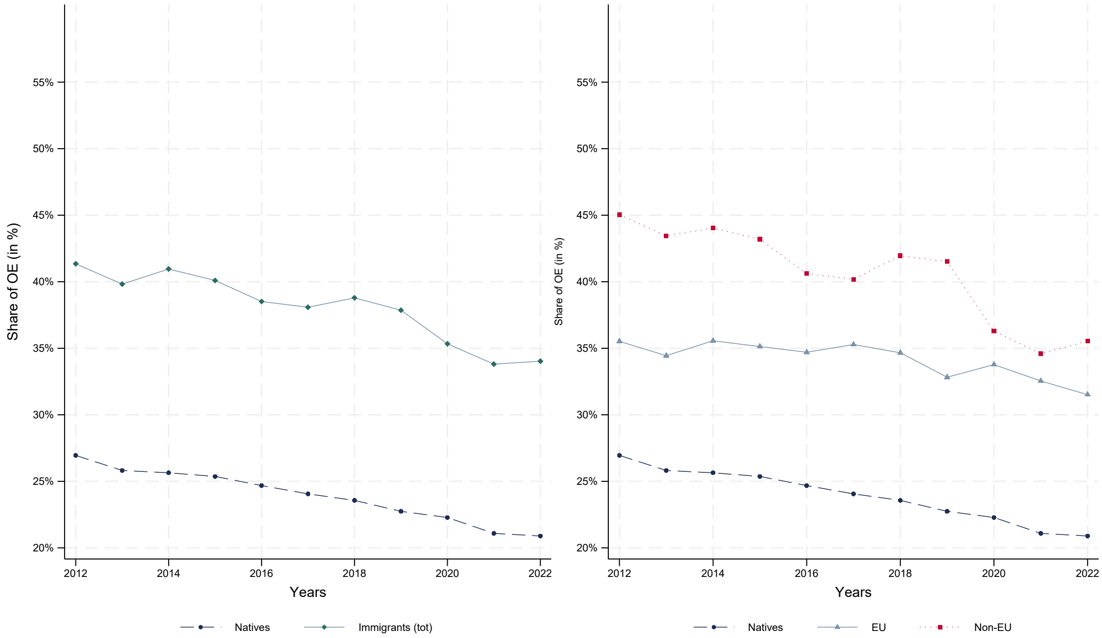
Figure 7: Evolution of overeducation shares for immigrants and natives



In Figure 8, we disaggregate immigrants into five areas of origin: the European Union, other European countries, Africa, America and Oceania, and Asia, and we display the overeducation shares for each group in all years. Differences in the level of overeducation are evident for each year, with immigrants from European countries outside the EU consistently having the highest shares of overeducation and those from the European Union exhibiting the lowest percentages. All areas of origin display a declining trend in overeducation over time.[4]

[4]Note that the sizeable jump in overeducation for "Other Europe" immigrants from 2019 to 2020 is likely driven by the change of status of UK migrants from "EU" to "non-EU" following Brexit (see section 4).

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Figure 8: Evolution of overeducation shares for immigrants, by area of origin

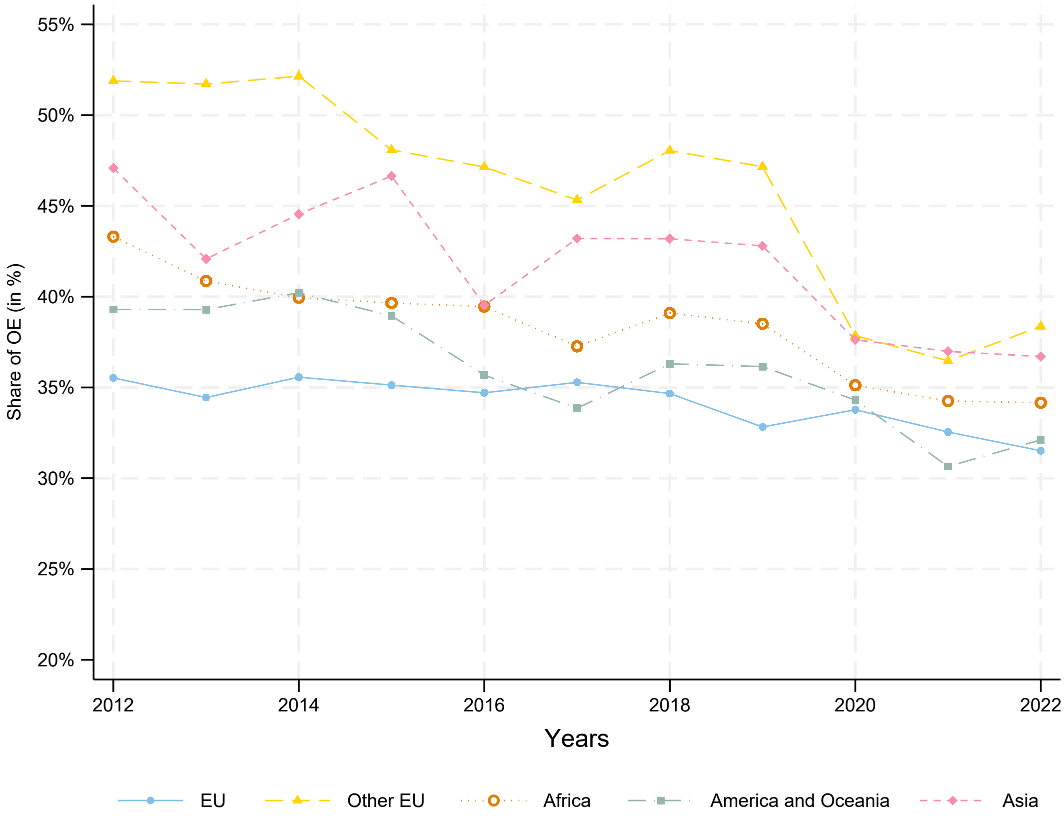

Figure 9 illustrates changes in overeducation shares among immigrants and natives, focusing on gender differences. The left graph displays the overeducation shares for female immigrants and natives, while the right side shows the same for males. In both graphs, solid lines represent immigrants, and dashed lines represent natives. Several key differences emerge from this graph. Firstly, native men generally have higher overeducation shares compared to native women. Conversely, women are slightly more likely to be overeducated among immigrants than men. As a result, the disparity in overeducation shares between immigrant and native women is considerably larger than the gap observed between immigrant and native men. This indicates that immigrant and native men have more similar probabilities

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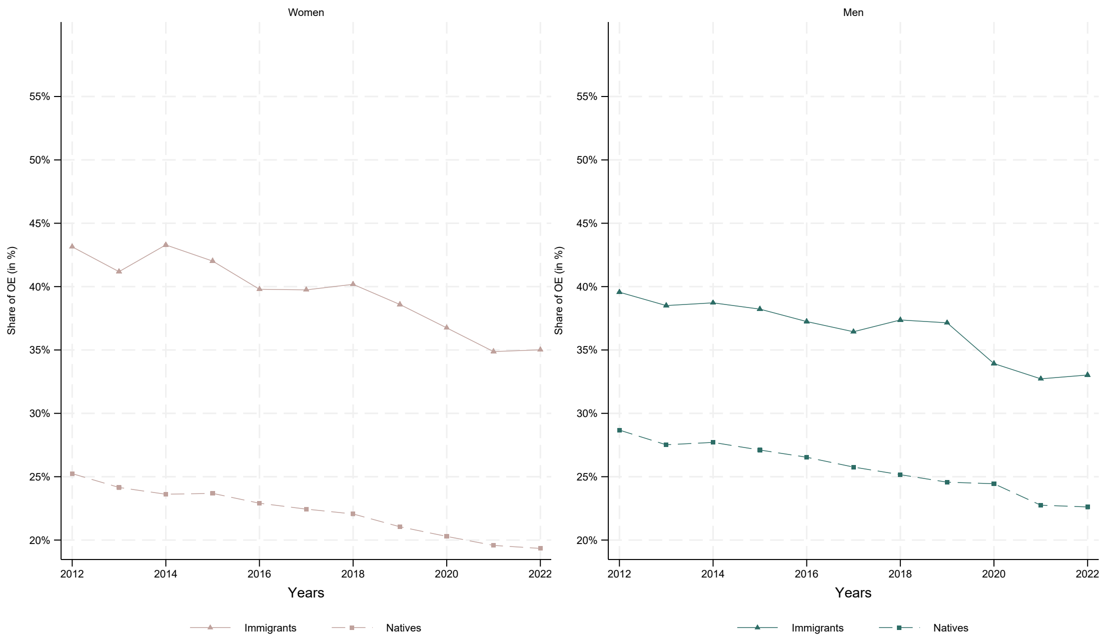
of overeducation compared to immigrant and native women.

Figure 9: Evolution of overeducation shares for immigrants and natives, by gender



5.1 Immigrant-Native Difference in Overeducation Probability

In the first part of this section, we showed that overeducation has declined across all population groups over time. This is partly mechanical: as the share of tertiary-educated individuals in the labour market increases, the likelihood of having tertiary-educated co-workers increases, *ceteris paribus*. Thus, to assess the degree of immigrants' overeducation, from now on, we will always report the percentage point differential in the overeducation probability between immigrants and natives. We obtain such a differential through the estimation of a regression equation, which also allows us to control for immigrant-native differences in factors such as geographic distribution across countries, age structure, and gender. Specifically, we estimate equations of the type:

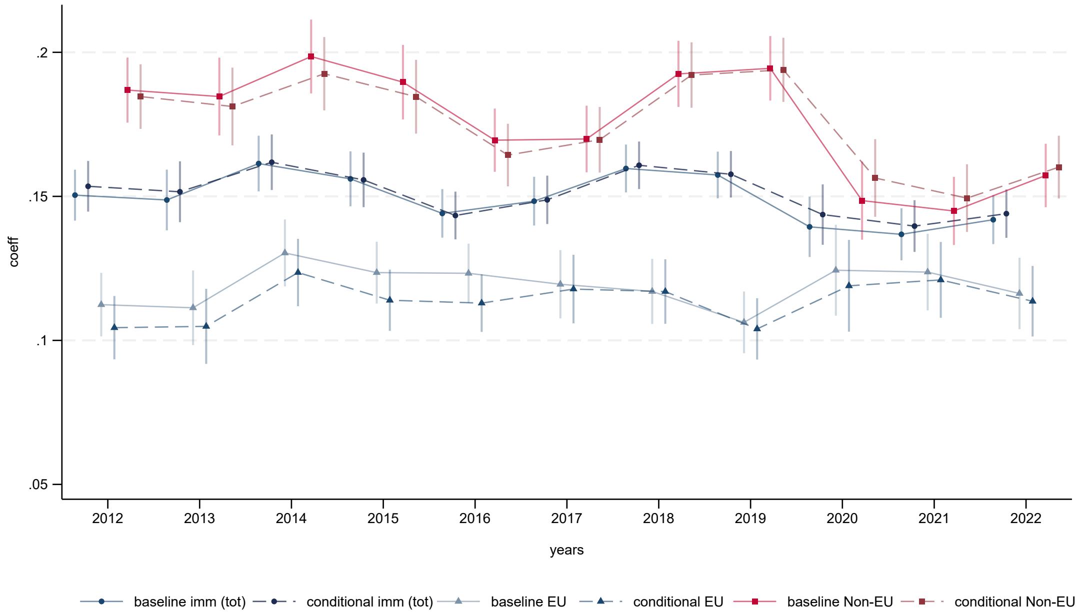
$$OE_{ict} = \sum_t \tau_t \times DY_t + \sum_t \beta_t imm_{ict} \times DY_t + \sum_c \gamma_c \times DC_c + X'_{ict}\delta + u_{ict} \qquad (1)$$

where OE_{ict} is a dummy, defined in section 2.3, which takes value 1 if individual i living in country c in year t is overeducated, and value 0 otherwise; DY_t are a set of year dummies; imm_{ict} is a dummy variable that identifies immigrants; $_c$ are a set of country dummies; finally X_{ict} is a vector of age (five-year age groups) and gender dummies.

We will estimate two versions of equation 1: the *baseline* version, which includes only the year dummies and their interaction with the immigrant dummy, and the *conditional* version, which includes the complete set of control variables. In both cases, we are interested in the estimate of β_t, which measures every year the percentage points difference in overeducation probability between immigrants and natives observed in the same year (in the *baseline* case), and the same differential between immigrants and natives observed in the same year and country and with same gender and age profile (in the *conditional* case).

From this point onwards, when we refer to overeducation, we will always refer to the overeducation probability differentials between immigrants and the reference group, i.e. natives.

Figure 10: Difference in OE probability (tot, EU, non-EU)



In Figure 10, the vertical axis represents the native-immigrant difference in the overeducation probability (β_t in equation 1), expressed in percentage points, while the horizontal axis displays the years. Detailed regression results are reported in Appendix Table A1. The total immigrant population is shown in blue, and the non-EU and EU immigrant groups are depicted in red and light blue, respectively. Solid lines represent estimates from our baseline model, whereas dashed lines indicate estimates from the conditional model.

The data reveals that immigrants in Europe are more likely to be overeducated than natives. This pattern persists even after accounting for demographic characteristics and time-invariant country characteristics. Indeed, both the baseline and the conditional model exhibit very similar trends. In 2022, the overeducation probability of immigrants was 14.4 p.p. higher than natives in the same country, age group, and gender. Such an overeducation differential has remained fairly stable around 15 p.p. over the years

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Among immigrants, those originating from outside the European Union are the most disadvantaged, with the gap in overeducation compared to natives reaching nearly 20 pp in some years. In contrast, immigrants from the EU experience lower overeducation differentials, with values consistently ranging between 10 and 12 percentage points.

Even though the difference in overeducation probability between natives and the overall immigrant population has remained relatively stable over time, a convergence between different immigrant groups appears to have occurred from 2019 onwards. In 2012, there was a relatively large difference between the two immigrant groups in terms of their overeducation differentials with natives. However, as the overeducation differential with natives increased for EU immigrants and decreased for non-EU immigrants, the gap between the two groups has diminished.

This pattern becomes clearer when examining Figure 11.[5] The immigrant sample is divided into five macro-areas of origin. We observe notable heterogeneity in immigrant-native overeducation differentials for each subgroup. In descending order, from the group with the highest difference in overeducation probability compared to natives to the group with the lowest, the categories are: immigrants originating from other European countries outside the EU, Asia, Africa, America and Oceania, and finally, from the European Union. While this ranking has remained relatively consistent over the years, the differences among the origin groups decreased significantly after 2019. Indeed, the differences among immigrants from Africa, Asia, and other European countries diminish to the point where they become nearly indistinguishable.

[5]We report only the conditional differentials for readability. Baseline differentials are very similar and reported in Appendix Figure A1. The corresponding regression results are reported in the Appendix Table A2.

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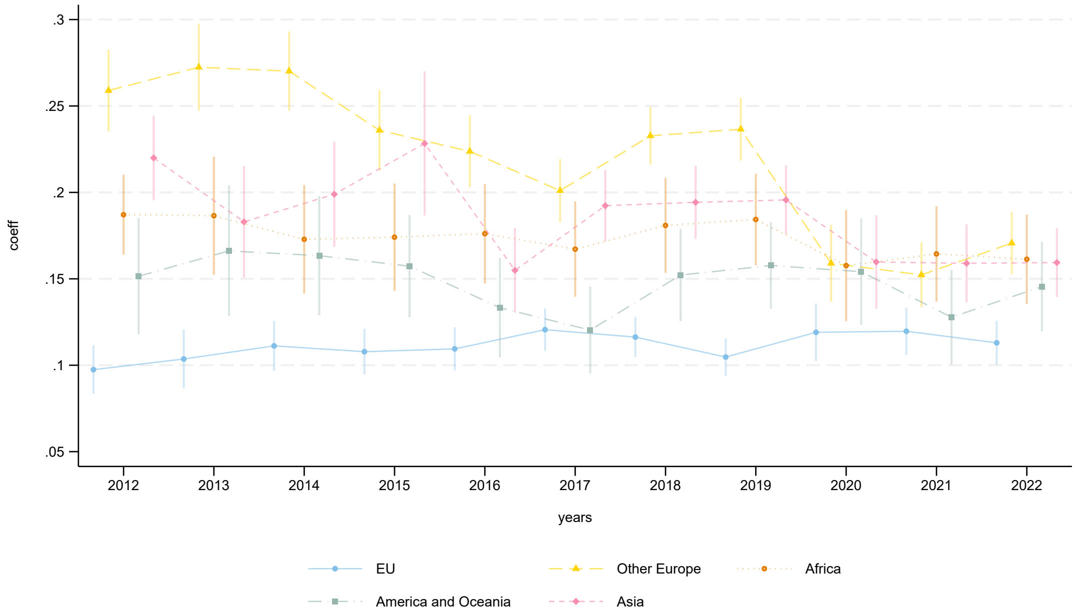
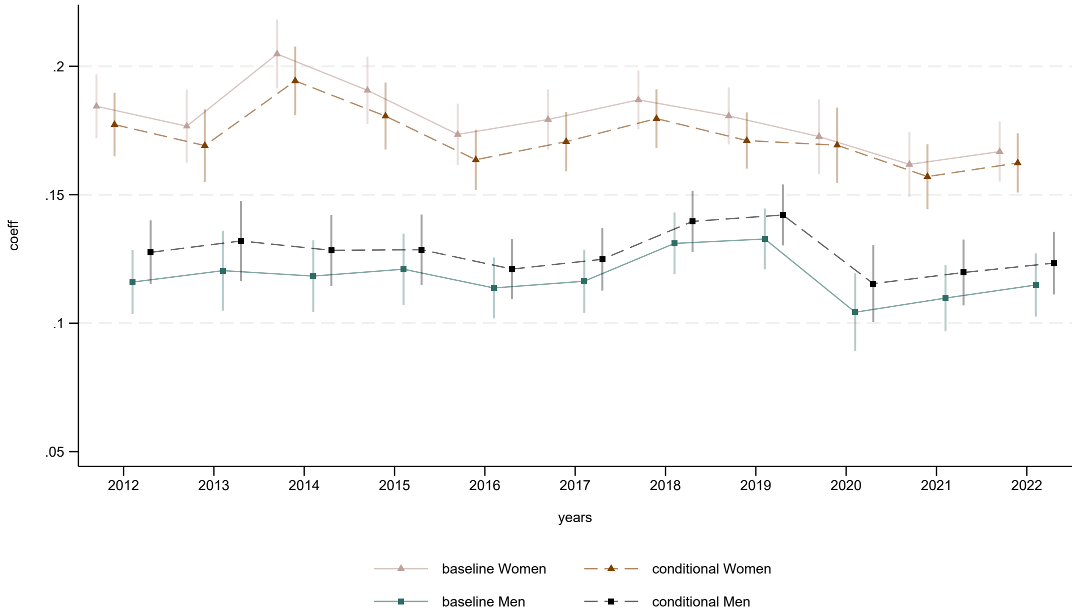
Figure 11: Conditional difference in overeducation probability by area of origin



In Figure 12, we look at the differences in overeducation probability between natives and immigrants, splitting the sample by gender into men and women (see Appendix Table A3 for full regression results). There are no significant changes over time, as the levels of overeducation differentials remain stable for both groups. The immigrant-native difference in the probability of overeducation is higher for women than for men. This is the same pattern that emerges from Figure 9 when looking at overeducation shares. In the baseline (conditional) model, the immigrant-native overeducation gap in 2022 was 16.7 (16.2) pp for women and 11.5 (12.3) pp for men.

Figure 12: Difference in overeducation probability by gender



5.2 Foreign- and Home-educated immigrants

Despite the increase in the percentage of highly educated individuals over the years for both immigrants and natives and the downward trend in overeducation shares across all subgroups, the immigrant-native overeducation differentials have remained relatively stable over time. This stability is observed regardless of country of origin or gender. However, one aspect we have neglected so far is the potential difference in overeducation between foreign- and domestically-educated immigrants relative to natives. While the former group has educational qualifications that may differ from those of natives in terms of content and quality (see Section 6) and may face hurdles in the formal recognition of their foreign degrees, these differences are not present for domestically-educated migrants. Therefore, any differential overeducation between domestically educated migrants and natives cannot be attributed to an intrinsic difference in the value of education but should be traced back

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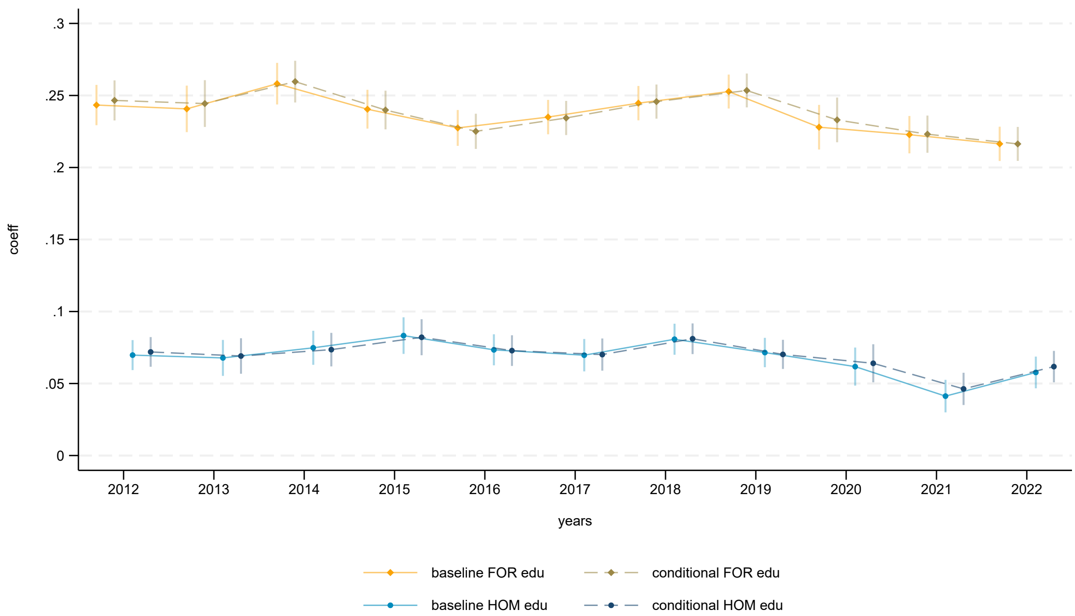
to other factors.

In this section, we investigate whether holding a foreign educational qualification influences the overeducation probability differentials between immigrants and natives.

Figure 13 shows clearly that foreign-educated immigrants have a significantly larger overeducation gap with respect to natives than home-educated immigrants every year (detailed regression results are reported in Appendix Table A4). The gap between foreign-educated immigrants and natives is more than three times the difference between home-educated immigrants and natives. In 2022, a tertiary-educated immigrant with a foreign qualification had a 21.6 p.p. higher probability of overeducation compared to a tertiary-educated native. In contrast, immigrants with domestic tertiary degrees were only about 5.8 pp more likely to be overeducated than natives. These differentials are not affected by controlling for country of residence, age group, and gender.

Figure 13: Difference in overeducation probability, by country of education



Similar differences between the overeducation of home- and foreign-educated migrants are visible also within different subgroups of the immigrant population.

In Figure 14, we observe the differences in overeducation probability for EU and non-EU immigrants, with the left figure showing data for foreign-educated immigrants and the right side for home-educated immigrants. Foreign-educated EU and non-EU immigrants display a similar pattern to that observed in Figure 10 for the entire immigrant sample, though the coefficients are slightly higher. In 2022, the conditional overeducation differentials for foreign-educated immigrants were 15 pp for EU and 25.9 pp for non-EU immigrants, with baseline estimates that are very similar. For home-educated immigrants, the impact of origin on the probability of overeducation compared to natives is less pronounced. Although non-EU immigrants still show higher levels of overeducation relative to EU immigrants in most years, the gap between the two groups narrows over time, disappearing from 2020 onwards.

Figure 14: Difference in overeducation probability, EU and non-EU migrants, by country of education

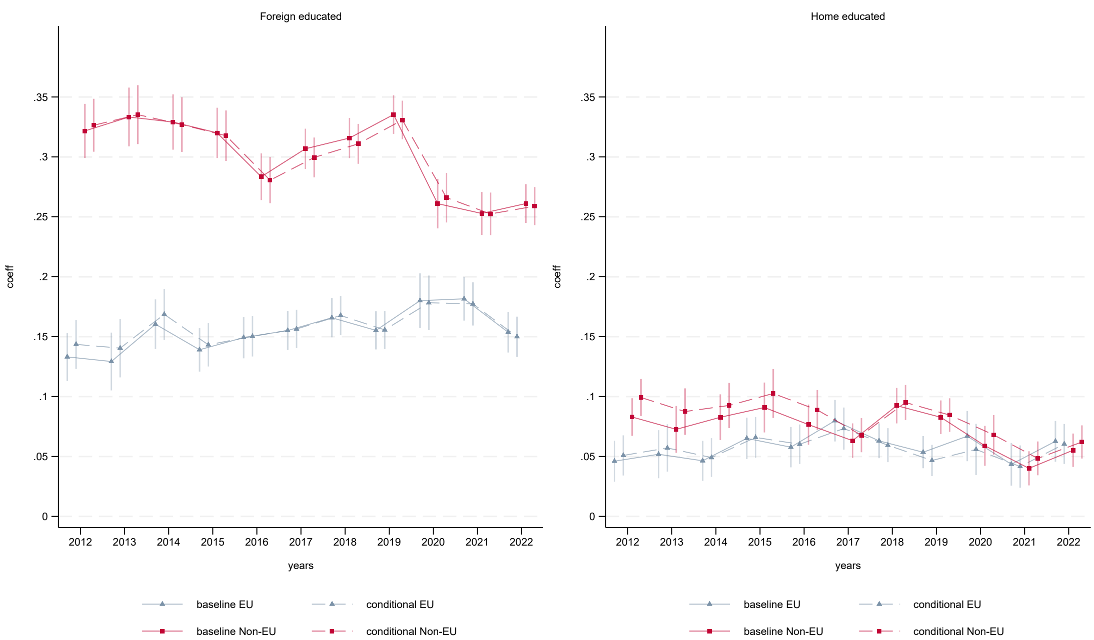


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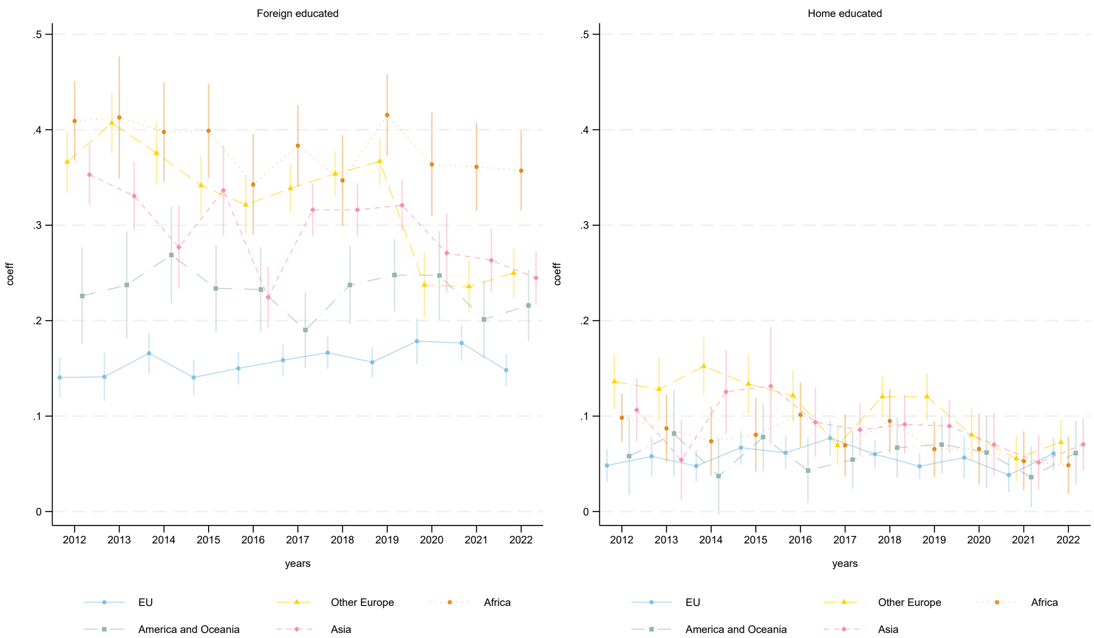
Figure 15 reports immigrant-native overeducation differential by country of education, further subdivided by area of origin.[6] Although confidence intervals are wider due to the small number of observations per category, the pattern observed in Figure 10 is still evident. Differences by country of origin are pronounced for foreign-educated immigrants. In contrast, for home-educated immigrants, these differences tend to diminish and level off.

Figure 15: Conditional difference in overeducation probability, by country of education and are of origin)



A similar pattern persists also when we distinguish between immigrant men and women. However, as shown in Figure 16, both foreign- and home-educated immigrant women have a higher overeducation probability compared to native women than their male counterparts. Although the gap between immigrant women and men narrows for home-educated immigrants, it remains noticeable and, although not always statistically significant at conventional

[6]For readability, we report only the conditional differentials. Baseline differentials are similar and reported in Appendix Figure A2.

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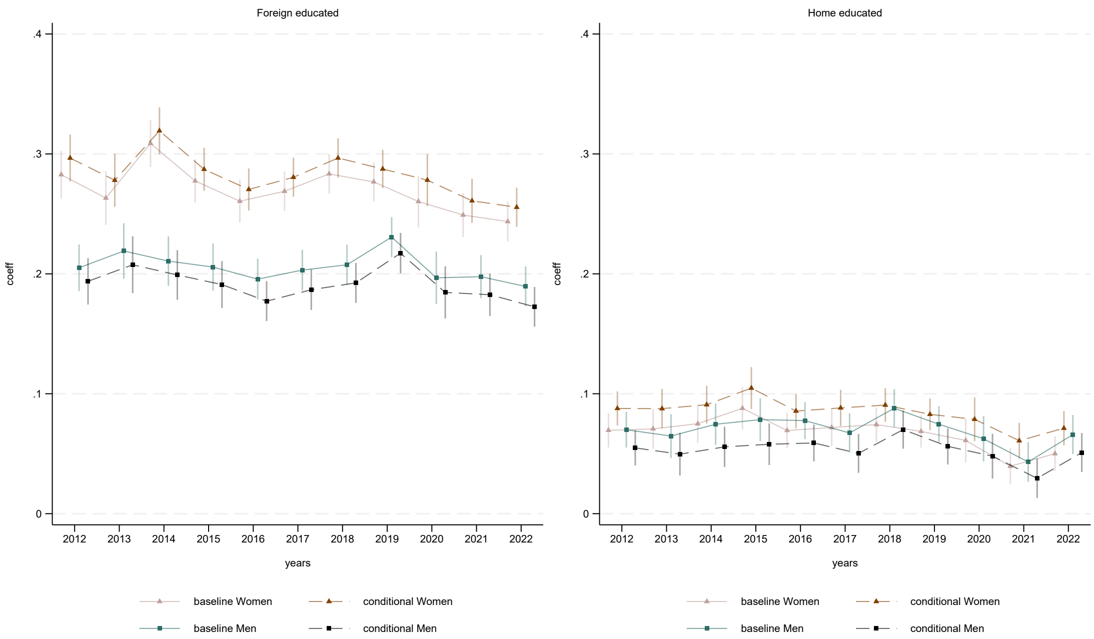
levels, it does not diminish over time.

Figure 16: Difference in overeducation probability, by country of education and gender



5.3 Years of potential experience

We have so far analysed how the immigrant-native differential in overeducation has evolved over time, between 2012 and 2022. For all years, we have compared the overeducation of all tertiary-educated immigrants to that of all tertiary-educated natives in Europe. In our *conditional* models, we have compared immigrants to natives in the same country and with the same gender and age profiles. However, we have neglected the fact that immigrants and natives might be at different stages of their (host country) labour market trajectories.

In this section, we study how immigrants' relative overeducation varies with years of experience in the labour market. To this end, we define a variable, "Years of potential experience," for immigrants and natives. For natives and home-educated immigrants, "Years of potential experience" is computed as the time elapsed since obtaining their highest level

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of education. For foreign-educated immigrants, instead, it is the number of years spent in the host country. After defining this variable, we estimate the following regression equation, pooling all years 2012–2022.

$$OE_{icet} = \sum_{e} \Big(\alpha_e EXP_{icet} + \beta_e foreduimm_{icet} \times EXP_{icet} + \gamma_e homeduimm_{icet} \times EXP_{icet} \Big) + \sum_{c,t} \delta_{ct} DC_c \times DY_t + X'_{ict}\phi + u_{ict} \tag{2}$$

where the notation is analogous to equation (1), EXP_{icet} are a set of dummies for each five-year potential experience interval e, and $foreduimm_{icet}$ and $homeduimm_{icet}$ are dummy variables denoting foreign- and home-educated immigrants respectively. In this case, too, we estimate two versions of equation (2). A *baseline* version where OE is regressed on a set of years of experience dummies and their interaction with $foreduimm$ and $homeduimm$, and a *conditional* version, which additionally includes the interaction of year and country fixed effects, as well as controls for age group and gender. In both cases, we are interested in the estimates of β_e and γ_e, which indicate respectively the percentage point differential in the probability of overeducation between foreign- and home-educated immigrants and natives in each group of labour market experience in the current country of residence. The graphs in this section display graphically the estimates of β_e and γ_e.

Figure 17 reveals an interesting relationship between overeducation differentials and years of potential experience. Overeducation differentials increase with experience up to a certain point, precisely 15-19 years, before starting to decline. This pattern is observed for both immigrant subgroups, though it is more pronounced for foreign-educated immigrants (see Appendix Table A5 for detailed regression results). For foreign-educated immigrants, the overeducation differential with natives more than doubles between the first and the

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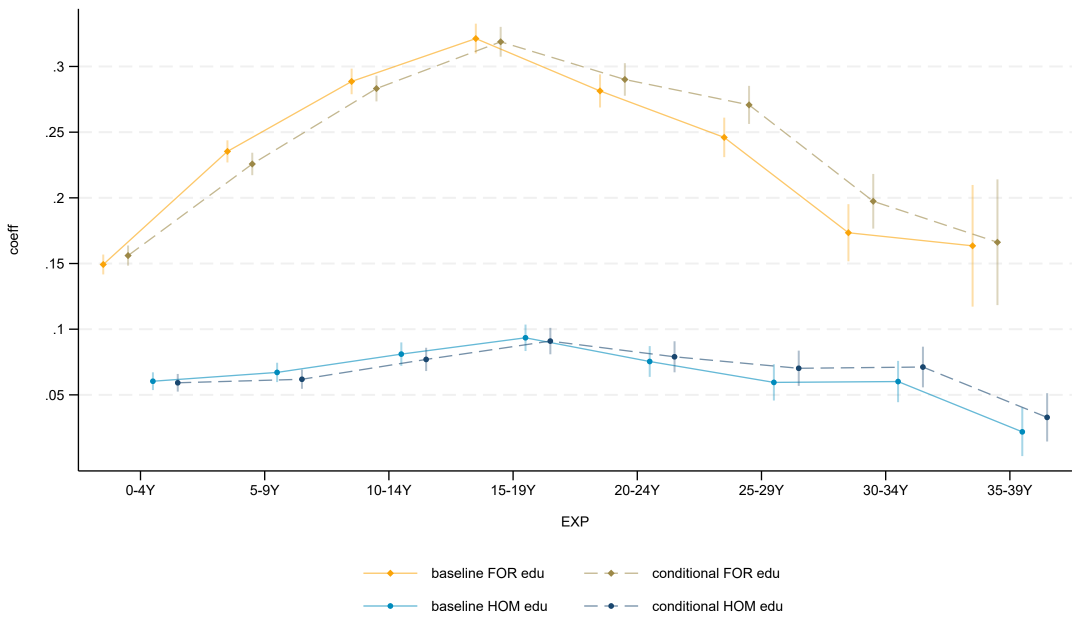
twentieth year of residence in the host country to the 20th year, rising from 14.9 pp to 32.2 pp. After reaching a peak after 15-19 years, the differentials begin to decrease, approaching the initial level among immigrants who have between 35 and 39 years of potential host country labour market experience. Home-educated immigrants display a similar evolution of their differential overeducation with experience, though the level is consistently lower, and the pattern is less pronounced. The overeducation differential relative to natives peaks at 15-19 years of potential experience, but the difference compared to the first year in the labour market is slightly above 3 percentage points (6 pp vs 9.3 pp).

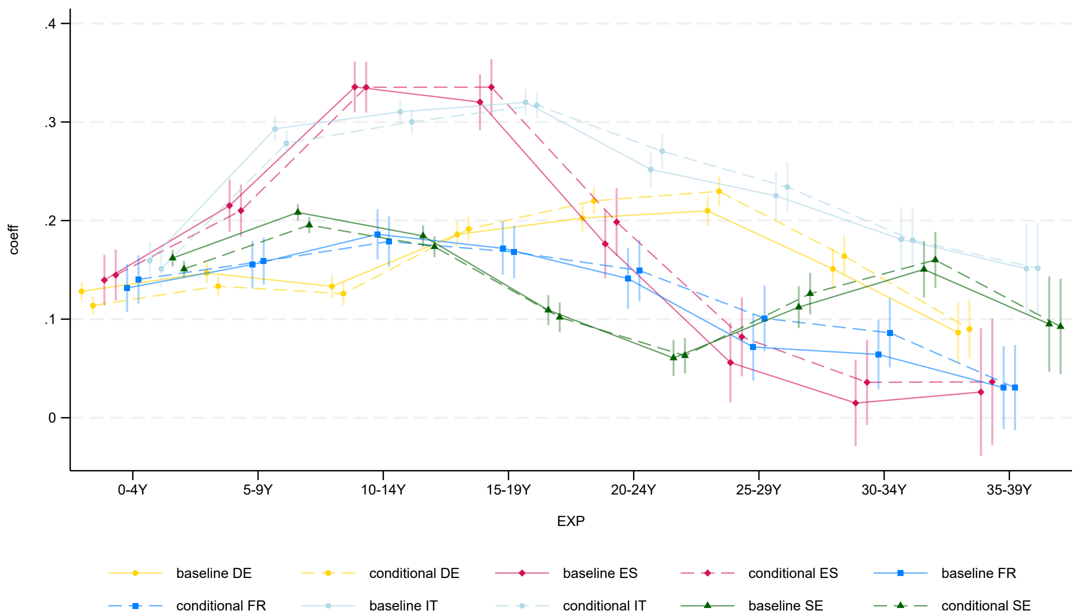
Figure 17: Difference in overeducation probability by experience and country of education



This inverted-U shape characterising the relationship between native–immigrant overeducation differentials and years of potential experience holds across different immigrant groups: as we show in the Appendix, it is present for both EU and non-EU immigrants (Figure A3) and for both men and women (Figure A4).

We can also replicate the same analysis on individual countries of residence, to determine whether the shape of the evolution of the overeducation differential is specific to certain countries. We focus on the four most populous countries in our sample (France, Germany, Italy and Spain) and on Sweden, which hosts a large share of immigrants in its population. Figure 18 illustrates that no single country drives this relationship. Instead, the pattern is evident in each of these five countries, although there are variations in the shapes and heights of the peaks. Italy and Spain are the countries where immigrants display the highest initial overeducation differentials, reaching their maximum after 10 to 19 years of experience. In Sweden and France, the curve is flatter, and the overeducation differential reaches its maximum after 5-14 years of host country labour market experience. The maximum overeducation differential in Germany is reached among immigrants who have been in the country for 25-29 years.

Figure 18: Difference in overeducation probability by experience (selected countries)



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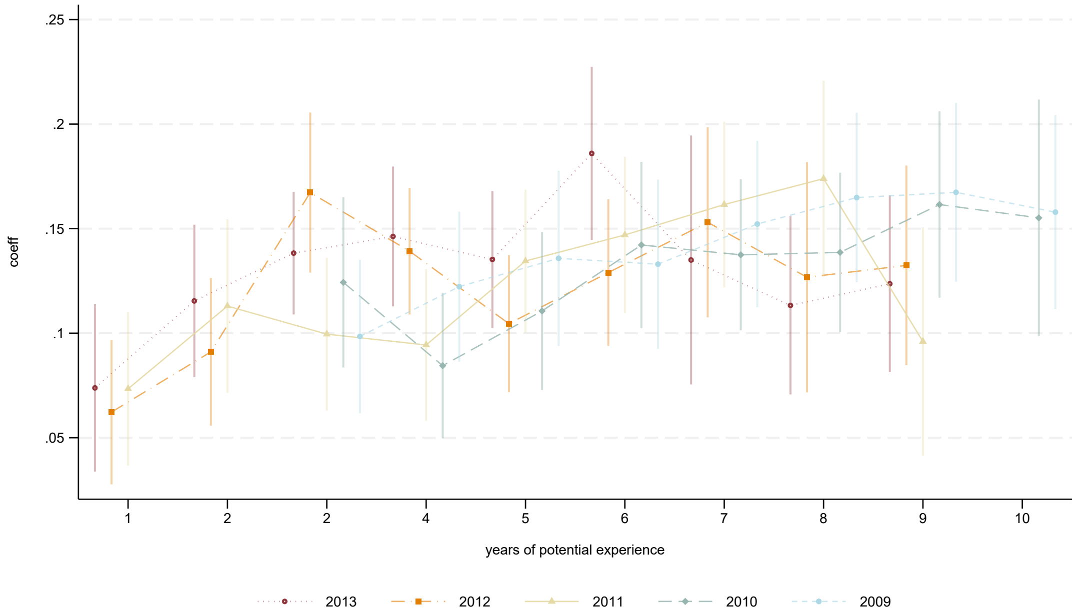
Note that all of the above analysis is based on repeated cross-sectional data. Thus, one concern is that the inverted U-shape relationship we have uncovered might be driven by differences across successive immigrant cohorts rather than describing the evolution of immigrants' labour market integration over time. To address this concern, we study the evolution of the immigrant-native overeducation differential for five different entry cohorts (2009, 2010, 2011, 2012 and 2013), which we are able to follow for at least eight complete years.[7] Although estimates are somehow noisy due to the small sample size, Figure 19 shows that all these five entry cohorts display similar levels of overeducation and the same evolution of their overeducation differential vis-a-vis natives: the percentage point difference in overeducation between immigrants and natives consistently increases during the first 9-10 years of potential experience, aligning with previous graphs.[8]

[7]Note that we cannot determine the precise year of entry in the country for immigrants who have been there for more than ten years (see section 3); hence we can only follow the same cohort for the first ten years in the host country.

[8]Figure 19 shows conditional differentials. Baseline differentials display a very similar pattern and are reported in Appendix Figure A5

Figure 19: Conditional difference in overeducation probability by experience and entry cohort



The findings of this section thus indicate that immigrants' overeducation tends to increase rather than decrease with the time spent in the host country's labour market. In other words, the acquisition of country-specific skills that typically happens with years since migration does not seem to increase the quality of the job matches until about fifteen to twenty years after migration. Since our analysis is based on cross-sectional data, however, this does not mean that the same employed immigrants are progressively less well educationally matched to their jobs with time spent in the host country. These findings suggest instead that there may be positive selection in the speed of job finding among tertiary-educated immigrants. Those who have "higher ability" might manage to find a job earlier than those who are lower down the ability distribution and are also more likely to find a better match for their education credentials.

6 Educational Quality

The measurement of formal overeducation may result in an overestimation of the actual underlying skill mismatch if the education received by individuals is of different quality and, hence, not comparable. This might be a particularly relevant issue when comparing educational qualifications obtained in different countries, which may be significantly different in terms of the quality of their educational systems. Our analysis so far has implicitly assumed that the quality of educational qualifications held by immigrants and natives was the same, but this may not be true. In this section, we will assess the role that differences in educational quality may play in explaining observed overeducation differences between foreign-educated immigrants and natives. We will use information on the country where individuals obtained their highest educational qualification — which is not available in the core EULFS dataset — together with different proxies of countries' educational quality.

6.1 Measurement

To assess the role of educational quality in explaining observed immigrant-native overeducation differentials, we need data on the country where individuals were educated and data on the quality of education in different countries.

The EULFS does not report information on the country of education. In section 5.2, we could only assess whether individuals completed their education before or after migrating. However, since we only have information on origin-country by macro-area (see section 3), we cannot precisely match immigrants to the quality of education in their country. Therefore, we cannot use the same data as in the previous section for this part of the analysis. The 2021 EULFS module on the "labour market situation of migrants and their immediate descendants" provides detailed information on the country where the highest education level

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was completed (variable *ahm2021_hatcntr*). Thus, the analysis in this section is based on 2021 cross-sectional data.

The data report information on 62,180 foreign-educated immigrants, defined as in section 5.2, out of which 21,766 are highly educated, i.e., with a university degree. Among them, we have information about the country where they completed their highest level of education (non-missing answer to the question) for 8,452 immigrants (39%). We matched them with a country-specific measure of education quality. For the rest of the foreign-educated migrants, assuming they obtained the highest educational qualification in their country of birth, we can only determine the macro-area where they were educated. Thus, for this group, we use a region-country of residence-specific weighted average of education quality, where the weights change across destination countries depending on the relative size of immigrants from each origin country (taken from the OECD International Migration Database).

We match the information on the country where individuals attained their highest educational qualification with alternative proxies of a country's academic quality, which we take alternatively from the *Harmonized Learning Outcomes Database* (HLO), the *Programme for the International Assessment of Adult Competencies* (PIAAC), and the *College Graduate Quality* (CGQ) measure from Martellini et al. (2024). The HLO provides a globally comparative learning outcome database across 164 countries for 2000-2017 (Angrist et al., 2021). We use the information on standardised test scores in mathematical (or alternatively in reading and science) for primary and secondary school students for each country to obtain a measure of learning outcomes that is comparable across countries (see Appendix B for more details on this and the other measures we use). Alternatively, we use data from the first cycle of the PIAAC *Survey of Adult Skills*, which measures over the period 2011-2018 literacy and numeracy skills of adults in 39 countries. Specifically, we compute the average literacy and

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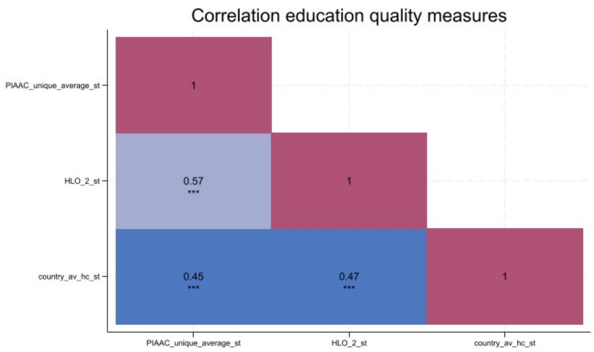
numeracy skills of all individuals with tertiary education in each country (ISCED levels 5A, 5B, and 6). Finally, we use data on college graduate quality (CGQ), computed in a recent paper by Martellini et al. (2024), which measures college quality based on returns to education from different colleges worldwide. Not all measures are available for all countries. Thus, we will replicate our estimates using each measure separately or using an average of all available measures for each country. As we will show later, the results are qualitatively similar in all cases.

Figure 20 shows that the three measures of educational quality are positively pairwise correlated, though the correlation is far from one, ranging between 0.36 and 0.59

Figure 20: Correlation Education Quality Measures



Overall, we matched information about education quality for 20,387 of the 21,766 immigrants highly educated abroad (94%).

6.2 Results

After matching individuals (both native and foreign-born) with a measure of their educational quality, we estimate overeducation differentials between foreign-educated immigrants and natives (we exclude home-educated immigrants from the sample for this part of the analysis).

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Our estimating equation is a slightly modified version of equation (1):

$$OE_{ioc} = \beta_0 + \beta_1 imm_{ioc} + \beta_2 EduQuality_{ioc} + \sum_c \gamma_c \times DC_c + X'_{ict}\delta + u_{ict} \tag{3}$$

where i indexes individuals, o the country where they were educated and c their country of residence. All variables have the same meaning as in previous sections. Additionally, $EduQuality$ is the measure of educational quality in country o (note that for natives $o = c$), and X_{ict} is a vector of control variables which includes quarter dummies, age, age squared and a gender dummy. Thus, β_1 measures the average percentage point difference in overeducation between foreign-educated immigrants and natives living in the same country and with similar characteristics after accounting for differences in educational quality.

Table 1 reports estimates of β_1 when equation (3) is estimated on different samples and with increasing control variables. The first line reports estimates from the full sample of foreign-educated immigrants and natives. In column (1), we display estimates from a model that includes only quarter and country dummies as control variables. In this specification, the overeducation of immigrants is estimated to be 23 pp higher than that of natives. In column (2), we add controls for individuals' age and gender. Including these control variables changes the estimate of β_1 only marginally, indicating that differences in demographic characteristics of immigrants and natives are not the driving force behind the differential overeducation (in line with the findings of the previous sections). In column (3), we instead control for educational quality, as proxied in this case by HLO. Including this variable reduces the estimated overeducation differential to 20 pp, indicating that differences in educational quality explain a part of the observed immigrant-native overeducation differential. Still, they are far from being its main explanation. The inclusion of demographic and educational quality controls in column (4) does not significantly affect the estimates. In the Appendix

(Tables A6, A7 and A8), we show that results using alternative measures of educational quality deliver qualitatively similar results.

The remaining rows of Table 1 report estimates of equation (3) from different population subgroups. First, in the second and third rows, we show overeducation differentials between EU and non-EU immigrants and natives, respectively. As we know, overeducation is higher among non-EU than EU immigrants. Furthermore, as expected, differences in educational quality matter more for the former than the latter group. The overeducation differential shrinks from 27 to 24 pp, a 12% reduction, for non-EU immigrants when we control differences in educational quality and demographics. Conversely, among EU immigrants, the overeducation differential vis-a-vis natives decreases only from 18 to 17 pp, a 4% reduction. This heterogeneity in the role of educational quality reflects the existence of larger differences in the quality of education between EU and non-EU countries than between the countries of origin of EU immigrants and their EU countries of destination. Finally, the last two rows report differentials separately for women and men. We again observe that the overeducation differential between immigrant and native women is higher than the corresponding differential among men. Nevertheless, the percentage reduction in the differential when differences in educational quality are controlled for is similar for both genders.

In Figure 21, we show, through a Gelbach decomposition (Gelbach, 2016), the role played by differences in individual characteristics and by differences in educational quality (measured with HLO) between immigrants and natives in explaining the overeducation differential. The Figure shows that 1.6% of the overall immigrant-native differential in overeducation can be explained by differences in demographics between the two groups, whereas an additional 12.8% can be traced back to differences in educational quality. Still, even after accounting for these differences, more than 85% of the differential overeducation remains

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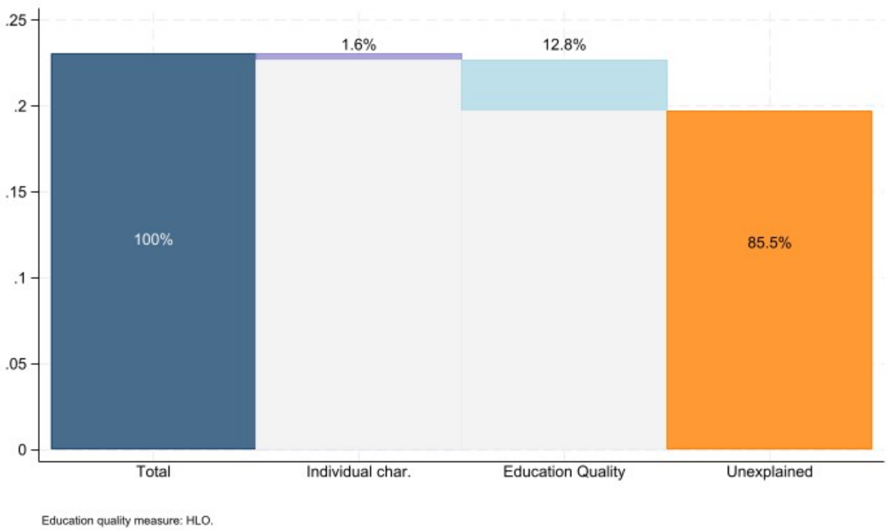
Table 1: Differences in overeducation probability, accounting for educational quality (HLO)

	(1)	(2)	(3)	(4)	N
All	0.231	0.226	0.199	0.197	255,160
	(0.007)	(0.007)	(0.008)	(0.008)	
EU imm.	0.179	0.175	0.174	0.172	246,230
	(0.010)	(0.010)	(0.010)	(0.010)	
Non-EU imm.	0.270	0.266	0.236	0.237	244,940
	(0.010)	(0.010)	(0.011)	(0.011)	
Females	0.266	0.260	0.231	0.229	141,313
	(0.010)	(0.010)	(0.011)	(0.011)	
Males	0.195	0.193	0.165	0.165	113,847
	(0.010)	(0.010)	(0.011)	(0.011)	
Quarters & Country Dummies	✓	✓	✓	✓	
Demographics		✓		✓	
Edu. Quality			✓	✓	

unexplained.[9]

Figure 21: Gelbach Decomposition of Immigrant-Native Gap in overducation



[9]In Appendix Figures A6, A7 and A8 we show that the use of alternative measures of educational quality does not affect this overall conclusion.

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7 Conclusions

This paper has investigated the persistent overeducation of tertiary-educated immigrants in European labour markets, focusing on the mismatch between their qualifications and job requirements. Using data from the European Labour Force Survey for the period 2012–2022, we have shown that immigrants, especially those from non-EU countries, are disproportionately overeducated compared to natives. Although overeducation has generally declined in recent years for all population groups, a significant immigrant-native gap endures, particularly for those who completed their education abroad. A notable finding is that for foreign-educated migrants, the risk of overeducation increases until after 15–19 years in the host country, suggesting that long-term integration does not automatically lead to better job-skill alignment. Future research with longitudinal data may allow a better understanding of the extent to which this is driven by a higher likelihood of overeducation for migrants who find a job later, by positively selected return migration, or by an occupational downgrading of the initially employed migrants.

The difference in the size and persistence of the immigrant-native overeducation gap between foreign-educated and domestically-educated migrants is one of the central results of this paper. Immigrants who completed their tertiary education in the host country are less likely to be overeducated relative to their foreign-educated co-nationals. This result indicates, therefore, that most immigrants' overeducation is due to the country where they acquired their education, rather than to immigrant status in itself. Surprisingly, however, our research has revealed that differences in educational quality between immigrants' home countries and their destination countries do not account for the majority of the overeducation gap. This suggests that the mismatch is likely influenced by other factors, such as barriers to recognising foreign qualifications, language difficulties, and limited access to career advancement opportunities in host countries. Identifying the role played by each of these factors in

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explaining the overeducation differential is a crucial area for future research.

Although more research is needed to precisely pin down the relative importance of each potential factor in explaining the persistence of immigrants' overeducation, these findings carry several important policy implications. First, improving the recognition of foreign qualifications and developing more efficient pathways for skill validation could help reduce overeducation among immigrants. Additionally, re-skilling and up-skilling initiatives tailored to immigrant workers and better early-career job placement programs could more effectively address the problem.

Future research should explore the institutional and structural factors that contribute to the persistence of overeducation among immigrants, such as national policies on labour market integration, immigration regulations, and the role of employers in recognising foreign qualifications. Evaluating the effectiveness of existing skill-matching programs and identifying best practices could provide further insights into reducing the immigrant-native overeducation gap.

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A Appendix Figures and Tables

Figures

Figure A1: Baseline difference in overeducation probability, by area of origin

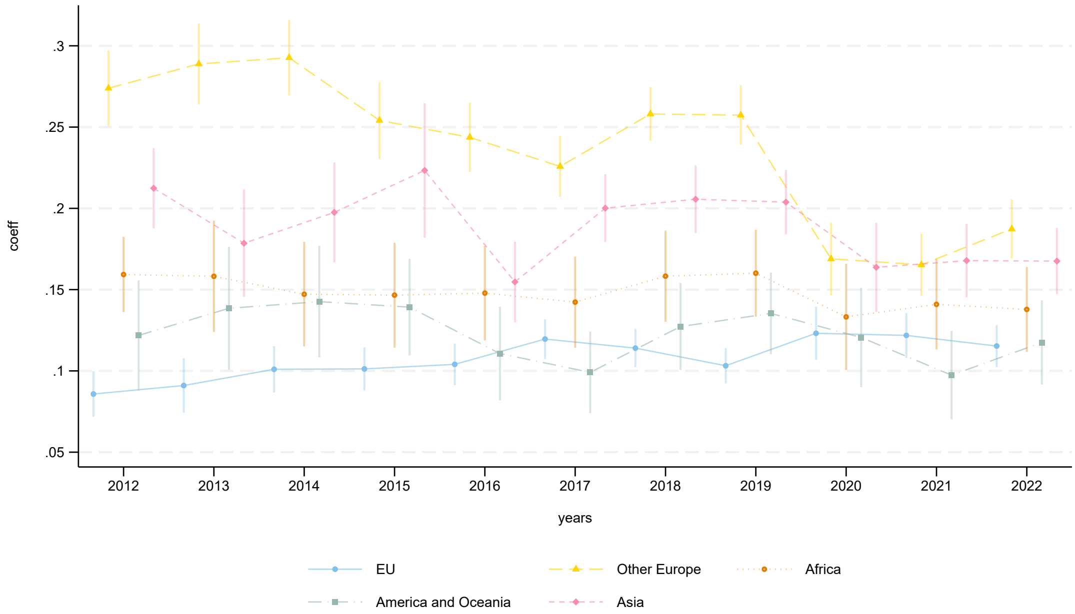

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Figure A2: Baseline difference in overeducation probability, by area of origin and country of education

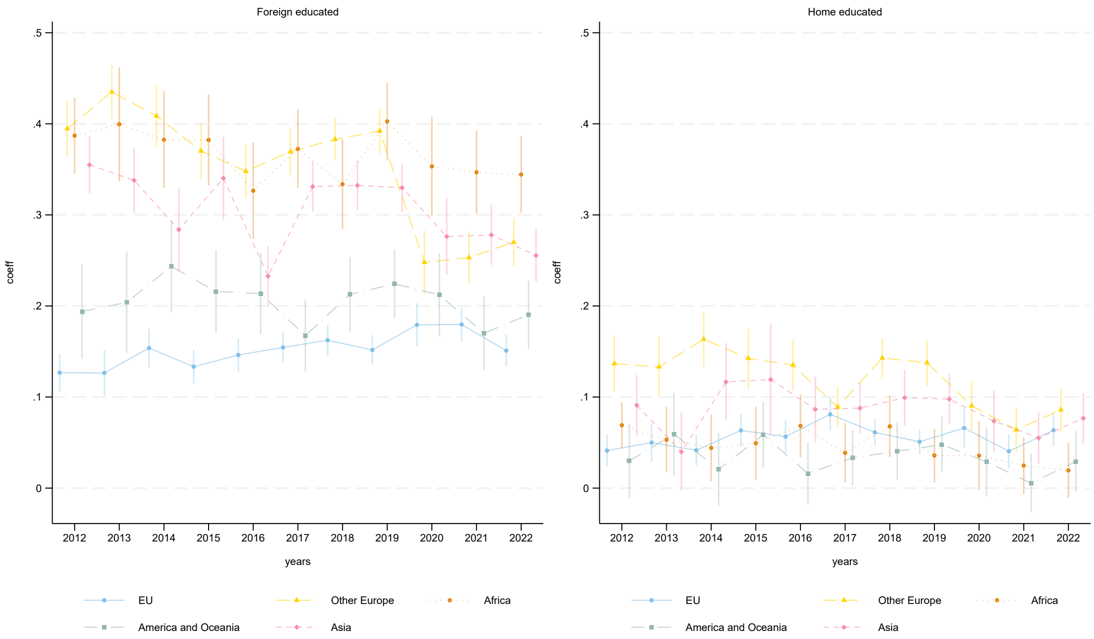

Figure A3: Difference in OE probability by EXP (EU, non-EU)

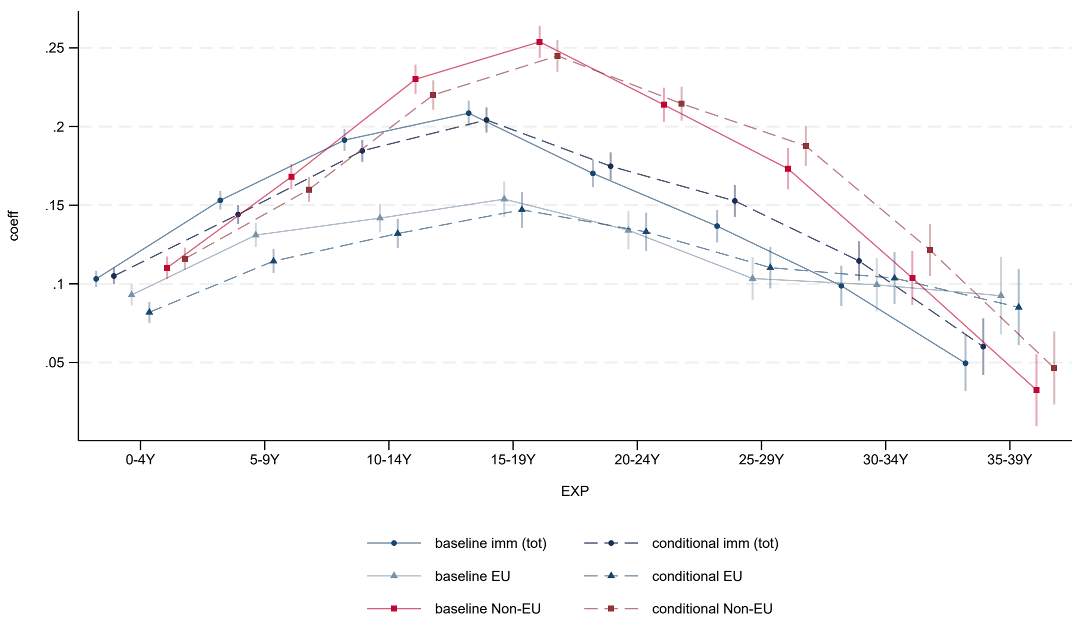

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Figure A4: Difference in OE probability by EXP (Women, Men)

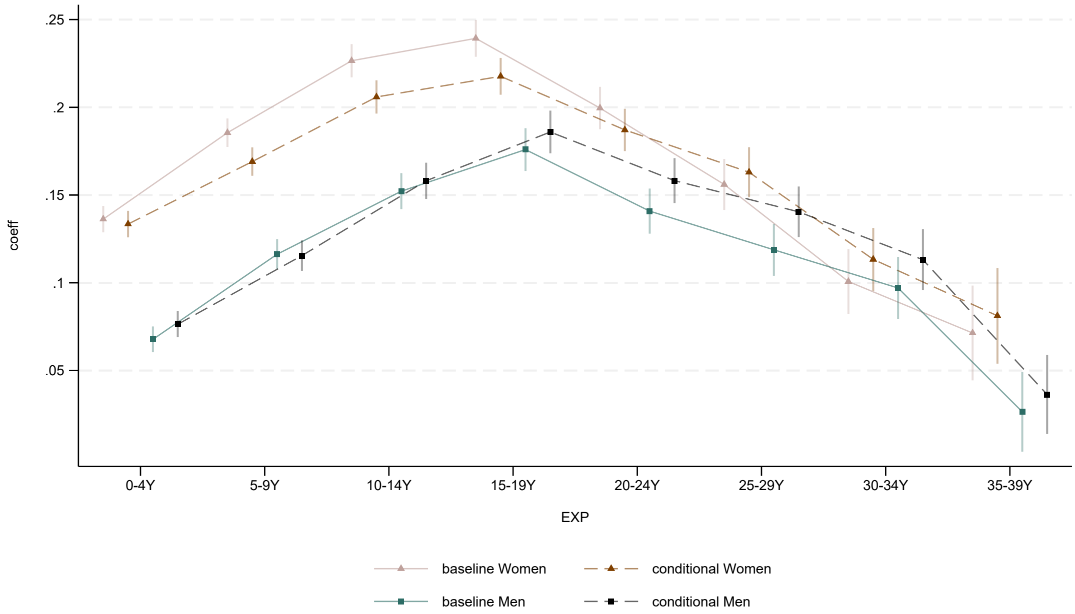


Figure A5: Baseline difference in overeducation probability by experience and entry cohort

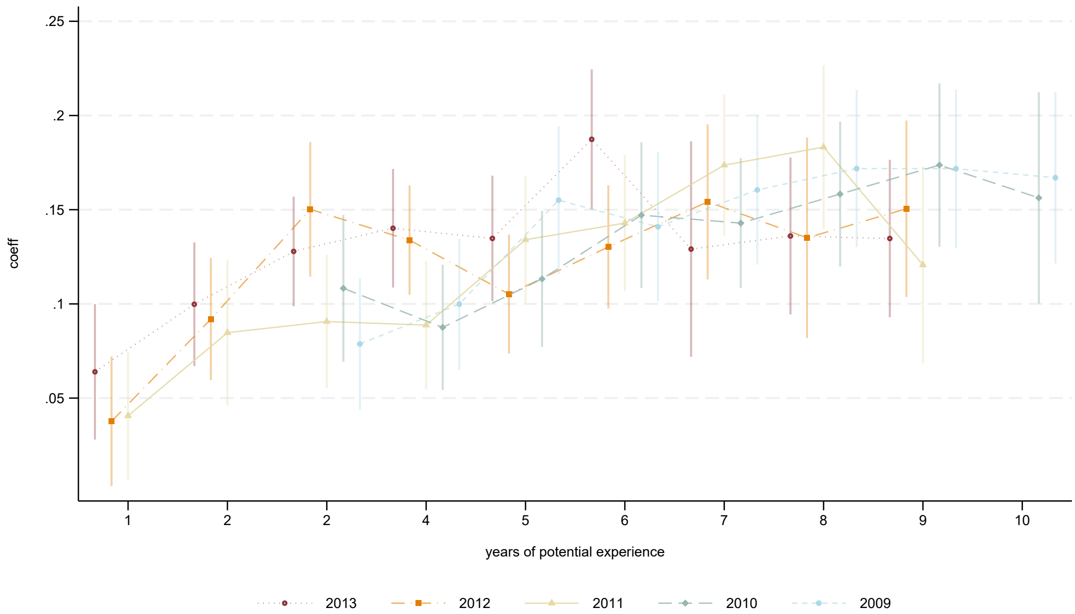
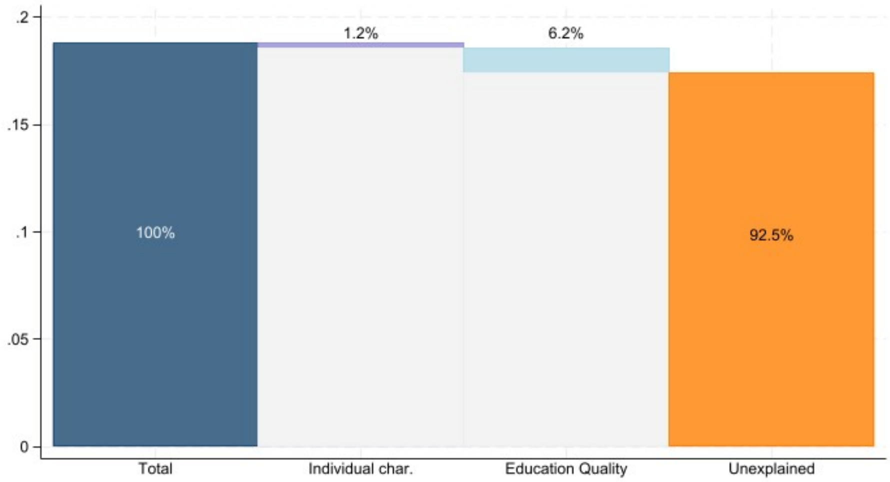
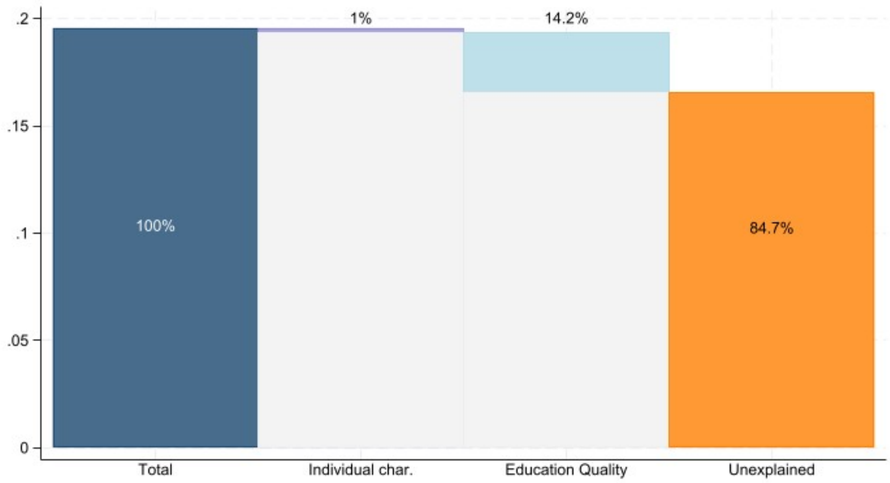


Figure A6: Gelbach Decomposition of Immigrant-Native Gap in overducation (edu qual: PIIAC)



Education quality measure: PIAAC.

Figure A7: Gelbach Decomposition of Immigrant-Native Gap in overducation (edu qual: ACQ)



Education quality measure: ACQ.

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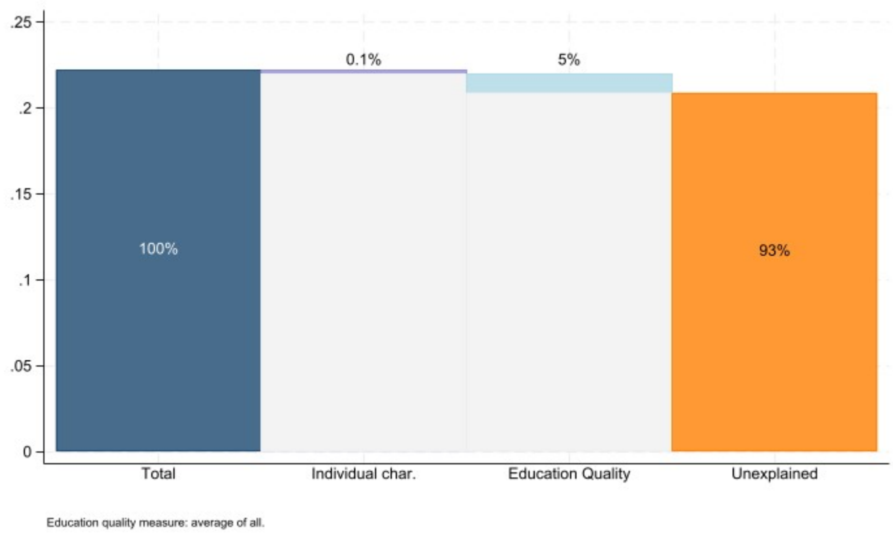
Figure A8: Gelbach Decomposition of Immigrant-Native Gap in overducation (edu qual: Average



Tables

Table A1: Regression results: Difference in OE probability (tot, EU, non-EU)

	Immigrants		EU immigrants		Non-EU immigrants	
VARIABLES	Baseline	Conditional	Baseline	Conditional	Baseline	Conditional
Immigrant#2012	0.150***	0.153***	0.112***	0.104***	0.187***	0.185***
	(0.005)	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)
Immigrant#2013	0.149***	0.152***	0.111***	0.105***	0.185***	0.181***
	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)	(0.007)
Immigrant#2014	0.161***	0.162***	0.130***	0.124***	0.199***	0.193***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.006)
Immigrant#2015	0.156***	0.156***	0.124***	0.114***	0.190***	0.185***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)
Immigrant#2016	0.144***	0.143***	0.123***	0.113***	0.169***	0.164***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)
Immigrant#2017	0.148***	0.149***	0.119***	0.118***	0.170***	0.170***
	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)
Immigrant#2018	0.160***	0.161***	0.117***	0.117***	0.193***	0.192***
	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)
Immigrant#2019	0.157***	0.158***	0.106***	0.104***	0.194***	0.194***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)
Immigrant#2020	0.139***	0.144***	0.124***	0.119***	0.149***	0.156***
	(0.005)	(0.005)	(0.008)	(0.008)	(0.007)	(0.007)
Immigrant#2021	0.137***	0.140***	0.124***	0.121***	0.145***	0.149***
	(0.005)	(0.005)	(0.007)	(0.007)	(0.006)	(0.006)
Immigrant#2022	0.142***	0.144***	0.116***	0.114***	0.157***	0.160***
	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Country	No	Yes	No	Yes	No	Yes
Gender	No	Yes	No	Yes	No	Yes
Age	No	Yes	No	Yes	No	Yes
Observations	4,377,663	4,377,663	4,132,381	4,132,381	4,138,271	4,138,271

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table A2: Regression results: Conditional difference in overeducation probability by area of origin

	EU		Other Europe		Africa		America and Oceania		Asia	
VARIABLES	Baseline	Conditional	Baseline	Conditional	Baseline	Conditional	Baseline	Conditional	Baseline	Conditional
Immigrant#2012	0.086***	0.097***	0.274***	0.259***	0.159***	0.187***	0.122***	0.151***	0.212***	0.220***
	(0.007)	(0.007)	(0.012)	(0.012)	(0.012)	(0.012)	(0.017)	(0.017)	(0.013)	(0.012)
Immigrant#2013	0.091***	0.104***	0.289***	0.272***	0.158***	0.187***	0.139***	0.166***	0.179***	0.183***
	(0.009)	(0.009)	(0.013)	(0.013)	(0.017)	(0.017)	(0.019)	(0.019)	(0.017)	(0.016)
Immigrant#2014	0.101***	0.111***	0.293***	0.270***	0.147***	0.173***	0.143***	0.163***	0.198***	0.199***
	(0.007)	(0.007)	(0.012)	(0.012)	(0.016)	(0.016)	(0.017)	(0.018)	(0.016)	(0.016)
Immigrant#2015	0.101***	0.108***	0.254***	0.236***	0.147***	0.174***	0.139***	0.157***	0.223***	0.228***
	(0.007)	(0.007)	(0.012)	(0.012)	(0.016)	(0.016)	(0.015)	(0.015)	(0.021)	(0.021)
Immigrant#2016	0.104***	0.109***	0.244***	0.224***	0.148***	0.176***	0.111***	0.133***	0.155***	0.155***
	(0.007)	(0.006)	(0.011)	(0.011)	(0.015)	(0.015)	(0.015)	(0.015)	(0.013)	(0.012)
Immigrant#2017	0.120***	0.121***	0.226***	0.201***	0.142***	0.167***	0.099***	0.120***	0.200***	0.192***
	(0.006)	(0.006)	(0.010)	(0.009)	(0.014)	(0.014)	(0.013)	(0.013)	(0.011)	(0.011)
Immigrant#2018	0.114***	0.116***	0.258***	0.233***	0.158***	0.181***	0.127***	0.152***	0.206***	0.194***
	(0.006)	(0.006)	(0.008)	(0.008)	(0.014)	(0.014)	(0.014)	(0.014)	(0.011)	(0.011)
Immigrant#2019	0.103***	0.105***	0.257***	0.237***	0.160***	0.184***	0.135***	0.158***	0.204***	0.196***
	(0.006)	(0.006)	(0.009)	(0.009)	(0.014)	(0.014)	(0.013)	(0.013)	(0.010)	(0.010)
Immigrant#2020	0.123***	0.119***	0.169***	0.159***	0.133***	0.158***	0.121***	0.154***	0.164***	0.160***
	(0.008)	(0.008)	(0.011)	(0.011)	(0.017)	(0.016)	(0.016)	(0.016)	(0.014)	(0.014)
Immigrant#2021	0.122***	0.120***	0.165***	0.152***	0.141***	0.164***	0.097***	0.128***	0.168***	0.159***
	(0.007)	(0.007)	(0.010)	(0.010)	(0.014)	(0.014)	(0.014)	(0.014)	(0.012)	(0.011)
Immigrant#2022	0.115***	0.113***	0.187***	0.171***	0.138***	0.161***	0.117***	0.145***	0.168***	0.159***
	(0.007)	(0.006)	(0.009)	(0.009)	(0.013)	(0.013)	(0.013)	(0.013)	(0.010)	(0.010)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Gender	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Age	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	3,576,137	3,576,137	3,423,089	3,423,089	3,391,353	3,391,353	3,387,021	3,387,021	3,400,674	3,400,674

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table A3: Regression results: Difference in overeducation probability by gender

	Female		Male	
VARIABLES	Baseline	Conditional	Baseline	Conditional
Immigrant#2012	0.184***	0.177***	0.116***	0.128***
	(0.006)	(0.006)	(0.006)	(0.006)
Immigrant#2013	0.177***	0.169***	0.120***	0.132***
	(0.007)	(0.007)	(0.008)	(0.008)
Immigrant#2014	0.205***	0.194***	0.118***	0.128***
	(0.007)	(0.007)	(0.007)	(0.007)
Immigrant#2015	0.191***	0.181***	0.121***	0.129***
	(0.007)	(0.007)	(0.007)	(0.007)
Immigrant#2016	0.173***	0.164***	0.114***	0.121***
	(0.006)	(0.006)	(0.006)	(0.006)
Immigrant#2017	0.179***	0.171***	0.116***	0.125***
	(0.006)	(0.006)	(0.006)	(0.006)
Immigrant#2018	0.187***	0.180***	0.131***	0.140***
	(0.006)	(0.006)	(0.006)	(0.006)
Immigrant#2019	0.181***	0.171***	0.133***	0.142***
	(0.006)	(0.006)	(0.006)	(0.006)
Immigrant#2020	0.173***	0.169***	0.104***	0.115***
	(0.007)	(0.007)	(0.008)	(0.008)
Immigrant#2021	0.162***	0.157***	0.110***	0.120***
	(0.006)	(0.006)	(0.007)	(0.007)
Immigrant#2022	0.167***	0.162***	0.115***	0.123***
	(0.006)	(0.006)	(0.006)	(0.006)
Year	Yes	Yes	Yes	Yes
Country	No	Yes	No	Yes
Age	No	Yes	No	Yes
Observations	2,345,099	2,345,099	2,032,564	2,032,564

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4: Regression results: Difference in overeducation probability, by country of education

VARIABLES	Foreign educated Baseline	Foreign educated Conditional	Home educated Baseline	Home educated Conditional
immigrant#2012	0.243***	0.247***	0.070***	0.072***
	(0.007)	(0.007)	(0.005)	(0.005)
immigrant#2013	0.241***	0.244***	0.068***	0.069***
	(0.008)	(0.008)	(0.006)	(0.006)
immigrant#2014	0.258***	0.260***	0.075***	0.074***
	(0.007)	(0.007)	(0.006)	(0.006)
immigrant#2015	0.240***	0.240***	0.083***	0.082***
	(0.007)	(0.007)	(0.006)	(0.006)
immigrant#2016	0.227***	0.225***	0.073***	0.073***
	(0.006)	(0.006)	(0.006)	(0.005)
immigrant#2017	0.235***	0.234***	0.070***	0.070***
	(0.006)	(0.006)	(0.006)	(0.006)
immigrant#2018	0.245***	0.246***	0.081***	0.081***
	(0.006)	(0.006)	(0.006)	(0.005)
immigrant#2019	0.253***	0.253***	0.072***	0.070***
	(0.006)	(0.006)	(0.005)	(0.005)
immigrant#2020	0.228***	0.233***	0.062***	0.064***
	(0.008)	(0.008)	(0.007)	(0.007)
immigrant#2021	0.223***	0.223***	0.041***	0.046***
	(0.007)	(0.007)	(0.006)	(0.006)
immigrant#2022	0.216***	0.216***	0.058***	0.062***
	(0.006)	(0.006)	(0.006)	(0.006)
Year	Yes	Yes	Yes	Yes
Country	No	Yes	No	Yes
Gender	No	Yes	No	Yes
Age	No	Yes	No	Yes
Observations	4,127,952	4,127,952	4,122,739	4,122,739

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table A5: Regression results: Difference in overeducation probability by experience and country of education

	Immigrants		EU immigrants		Non-EU Iimmigrants	
VARIABLES	Baseline	Conditional	Baseline	Conditional	Baseline	Conditional
EXP_class(0-4Y)#immigrant	0.103***	0.105***	0.093***	0.082***	0.110***	0.116***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
EXP_class(5-9Y)#immigrant	0.153***	0.144***	0.131***	0.114***	0.168***	0.160***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
EXP_class(10-14Y)#immigrant	0.191***	0.185***	0.142***	0.132***	0.230***	0.220***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
EXP_class(15-19Y)#immigrant	0.209***	0.204***	0.154***	0.147***	0.254***	0.245***
	(0.004)	(0.004)	(0.006)	(0.006)	(0.005)	(0.005)
EXP_class(20-24Y)#immigrant	0.170***	0.175***	0.134***	0.133***	0.214***	0.215***
	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)
EXP_class(25-29Y)#immigrant	0.137***	0.153***	0.103***	0.110***	0.173***	0.188***
	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)	(0.007)
EXP_class(30-34Y)#immigrant	0.099***	0.115***	0.099***	0.104***	0.104***	0.121***
	(0.007)	(0.006)	(0.009)	(0.008)	(0.009)	(0.008)
EXP_class(35-39Y)#immigrant	0.050***	0.060***	0.092***	0.085***	0.033***	0.046***
	(0.009)	(0.009)	(0.013)	(0.012)	(0.012)	(0.012)
EXP_class	Yes	Yes	Yes	Yes	Yes	Yes
Country#Year	No	Yes	No	Yes	No	Yes
Year	No	No	No	No	No	No
Gender	No	Yes	No	Yes	No	Yes
Age	No	Yes	No	Yes	No	Yes
Observations	4,377,663	4,377,663	4,132,381	4,132,381	4,138,271	4,138,271

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table A6: Differences in overeducation probability, accounting for educational quality (PIAAC)

Edu qual: PIAAC	(1)	(2)	(3)	(4)	N
All	0.188	0.186	0.177	0.174	288,399
	(0.007)	(0.007)	(0.008)	(0.008)	
EU imm.	0.158	0.156	0.145	0.142	280,491
	(0.009)	(0.009)	(0.011)	(0.011)	
Non-EU imm.	0.217	0.215	0.217	0.214	278,292
	(0.010)	(0.010)	(0.012)	(0.012)	
Females	0.214	0.211	0.200	0.196	158,152
	(0.010)	(0.010)	(0.011)	(0.011)	
Males	0.161	0.159	0.152	0.150	130,247
	(0.010)	(0.010)	(0.012)	(0.012)	
Quarters & Country Dummies	✓	✓	✓	✓	
Demographics		✓		✓	
Edu. Quality			✓	✓	

Table A7: Differences in overeducation probability, accounting for educational quality (ACQ)

Edu qual: ACQ	(1)	(2)	(3)	(4)	N
All	0.196	0.194	0.169	0.166	286,987
	(0.007)	(0.007)	(0.009)	(0.009)	
EU imm.	0.169	0.166	0.144	0.142	278,476
	(0.009)	(0.009)	(0.012)	(0.012)	
Non-EU imm.	0.218	0.216	0.200	0.198	276,854
	(0.010)	(0.010)	(0.013)	(0.013)	
Females	0.225	0.222	0.188	0.184	157,137
	(0.010)	(0.010)	(0.013)	(0.013)	
Males	0.166	0.164	0.148	0.146	129,850
	(0.010)	(0.010)	(0.013)	(0.013)	
Quarters & Country Dummies	✓	✓	✓	✓	
Demographics		✓		✓	
Edu. Quality			✓	✓	

Table A8: Differences in overeducation probability, accounting for educational quality (average)

Edu. Quality Average	(1)	(2)	(3)	(4)	N
All	0.222	0.220	0.211	0.209	297,779
	(0.007)	(0.007)	(0.008)	(0.008)	
EU imm.	0.178	0.176	0.177	0.174	288,492
	(0.010)	(0.010)	(0.010)	(0.010)	
Non-EU imm.	0.253	0.251	0.242	0.241	287,468
	(0.009)	(0.009)	(0.011)	(0.012)	
Females	0.255	0.252	0.241	0.242	163,616
	(0.010)	(0.010)	(0.012)	(0.012)	
Males	0.189	0.188	0.180	0.175	134,163
	(0.010)	(0.010)	(0.012)	(0.012)	
Quarters & Country Dummies	✓	✓	✓	✓	
Demographics		✓		✓	
Edu. Quality			✓	✓	

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B Appendix: Educational Quality Measures

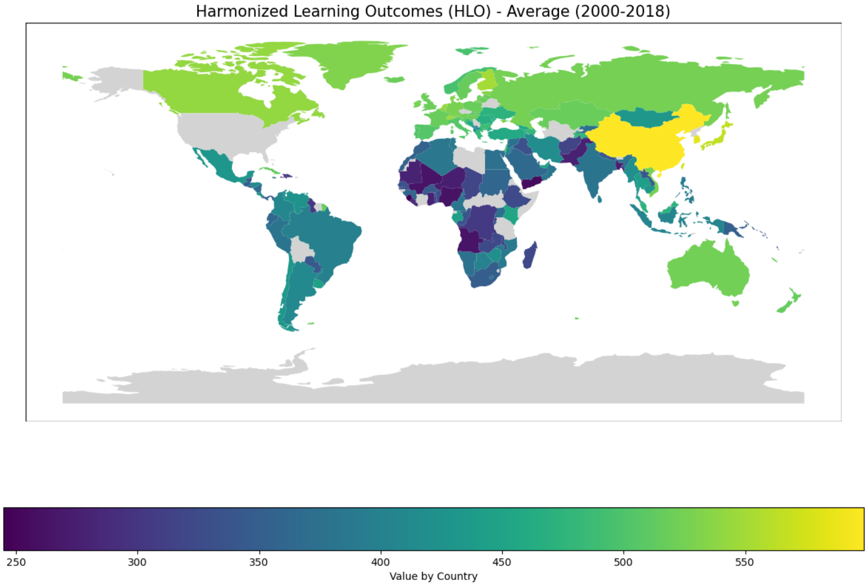
This Appendix provides details about the three measures of educational quality used in the paper.

B.1 Harmonized Learning Outcomes (HLO)

The first measure of education quality used comes from the Harmonized Learning Outcomes (HLO) Database (Angrist et al., 2021). The HLO provides a globally comparable database of 164 countries from 2000 to 2017, covering 98% of the global population. Developing economies comprise two-thirds of the included countries. Using the HLO, we construct a measure of educational quality based on math test scores in primary and secondary education for all countries. For the country-years in which primary and secondary education scores are available, we take an average of the two. We use reading test scores instead for country-years, where math scores are not available. If reading scores are not available either, we use science test scores. When scores for a country are not available in a year, we use the value for the closest available year.

Figure B1 shows the countries for which we can construct a measure of education quality based on HLO.

Figure B1: HLO Coverage



B.2 Survey of Adult Skills (PIAAC)

Our second measure of education quality is based on PIAAC data. The PIAAC (*Programme for the International Assessment of Adult Competencies*) is a programme of assessment and analysis of adult skills, whose major output is the *Survey of Adult Skills*, an international computer-based household survey of adults aged 16-65. The Survey aims to measure adults' proficiency in key information-processing skills (literacy, numeracy, and problem-solving) and gather information and data on how adults use their skills at home and work. The Survey is organized in cycles, and the first one was conducted over three separate rounds between 2011 and 2018 in 39 countries, interviewing about 245,000 adults, representing 1.15 billion people. We construct our measures of educational quality for each country as an average of literacy and numeracy scores for tertiary-educated individuals living there.

Figure B2 shows the countries for which we can construct a measure of education quality based on HLO.

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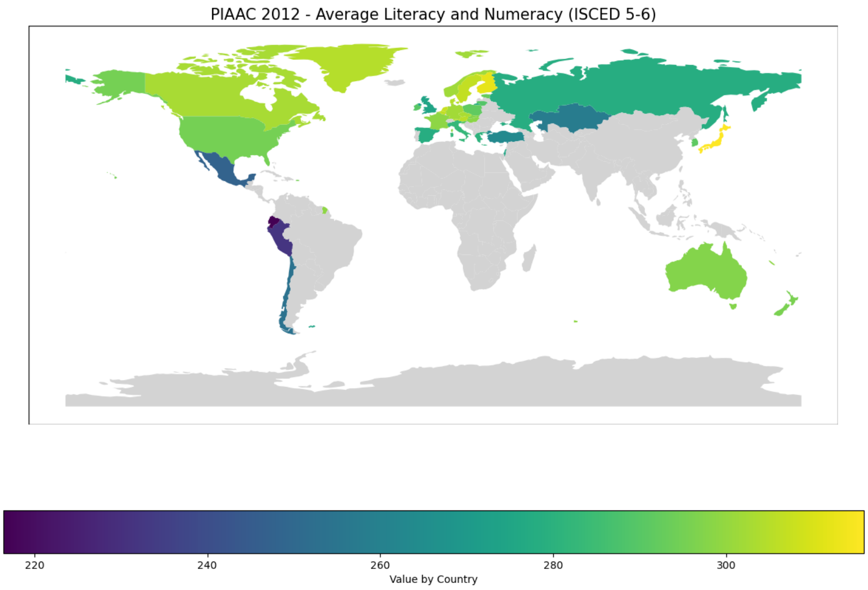
Figure B2: PIAAC 2012 Coverage



B.3 College Graduate Quality

Our third measure of education quality is based on the measure of *college graduate quality* (CGQ) proposed by Martellini et al., 2024. This measure builds on the fact that under standard assumptions, the average human capital of a college's graduates is proportional to their average earnings. The authors use data (from the website Glassdoor) on the earnings of migrants who work in multiple countries to estimate the effect of country, skill portability, and selection on comparative advantage in earnings. They then adjust workers' earnings to capture what each worker would earn in a common labour market. Finally, they take the average of these adjusted earnings by alma mater to measure college graduate quality. We average these data by country to obtain a country-level measure of college quality.

Figure B3 shows the countries for which we can construct a measure of education quality based on HLO.

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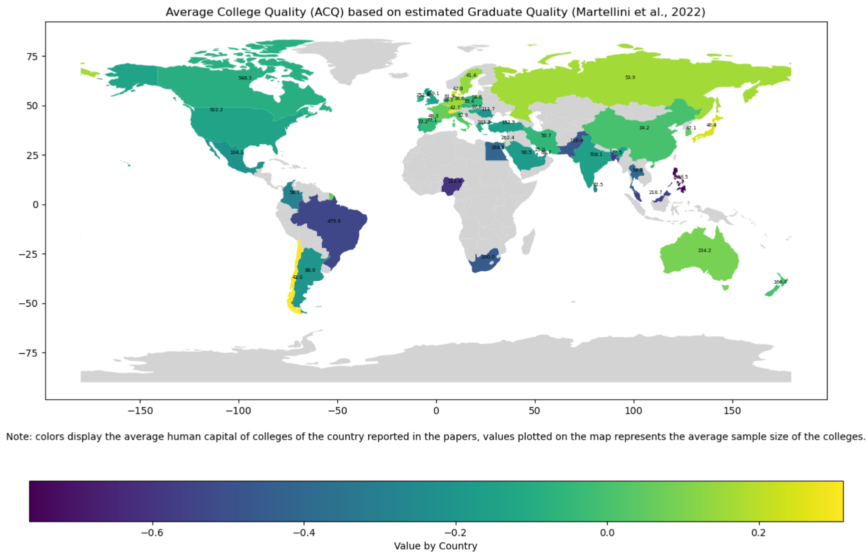
Figure B3: College Graduate Quality Coverage



GS4S Working paper series (D7.3)

Working paper no. 2

The Overeducation of Immigrants in Europe

About GS4S

GS4S seeks to better understand global skills shortages in selected sectors (Digital, Care and Construction) and strengthens evidence-based and multi-level policies on labour migration governance. The project provides new knowledge on alternative and equitable ways for addressing skills shortages in six regions (EU, EEA, Western Balkan, Middle East and Northern Africa, West Africa, and South/South-East Asia).

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