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D6.3 Educational Mismatch and Migrant Assimilation in Western Europe

WP6 Assessing european labour market inequalities from different perspectives

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Summary

This study examines the process of immigrant assimilation by documenting, and analysing, educational mismatch in Western European countries before and after the Great Recession of 2008/09. Our focus is on the education-job mismatch, a crucial dimension often overlooked in studies about immigrant assimilation. Our analysis, which distinguishes between men and women, pays due attention to the unique institutional framework of each country and aims to shed light on the process of convergence between migrants and natives. The empirical results reveal sharp differences in educational mismatch between migrants and natives in the year of arrival. These are particularly pronounced among women. What is more, these differences between migrants and natives become even bigger over the first few years after arrival, and narrow only afterwards. This points to substantial and long-lasting challenges in the assimilation of migrants. Finally, and perhaps surprisingly, we find little evidence for a prominent role of macroeconomic conditions and attitudes of natives towards migrants in the assimilation process.

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1 Introduction

The economic outcomes of migrants are significantly influenced by their effective integration into the labour market of the host country. The greater the success of immigrants in the labour market, the more substantial their net economic and fiscal contributions to the host economy. This, in consequence, can shape the attitudes of the native population towards immigrants. It can also have implications for immigration policies. Conversely, economic struggles may result in the social and economic exclusion of immigrants and their descendants, potentially leading to social unrest.

In this paper, we shed light on the process of migrant assimilation in the labour market by examining the mismatch between migrants' education and their jobs. Mismatch of this kind can lead to reduced job satisfaction and disengagement, ultimately affecting migrants' economic performance and productivity. Educational mismatch in the form of overeducation contributes to widening inequalities with respect to the native-born population, by limiting migrants' access to quality employment opportunities and thereby undermining their integration into the host country. Overall, mismatch as presented in search and matching theory is a short-run phenomenon caused by imperfect information in the labour market (Groot & Maassen van den Brink, 2000; Chiswick & Miller, 2009). Workers enter the labour market with imperfect knowledge about their abilities to acquire different types of skills and to learn over time. Matching efficiency is expected to improve over time as workers adjust their occupational choices using the accumulated information about their skills. While this adjustment from an imperfect match to a better one is common to all workers, it is expected to be slower for immigrants because of the multiple disadvantages they face compared to natives. First, lack of language skills may push immigrants down the occupational ladder into jobs for which they are overeducated. Second, the low transferability of foreign education to domestic skills may lead some employers to disregard or undervalue immigrants' previous educational attainment. Third, immigrants may be more economically constrained than natives because, depending on the host country's unemployment benefit systems and migration policies, an immigrant may be more willing to accept a job that does not match his or her abilities.

The integration of migrants is usually approached through their economic assimilation by measuring the gap with natives along several labour market outcomes and tracing the evolution of this gap over time (e.g., Chiswick (1978); Borjas (1985); Lubotsky (2007); Algan et al. (2010); Abramitzky et al. (2014); Ho & Turk-Ariss (2018); Lee et al. (2022)). These studies highlight significant earnings disadvantages and different employment probabilities for migrants, with the rate of convergence influenced by factors such as the country of origin, the country of destination, and the migrant cohort. This phenomenon is associated with disparities in the distribution of employment across occupations and with lower returns to education for migrant workers. According to human capital theory (Mincer, 1974), immigrants are likely to experience a significant earnings and employment gap with natives upon arrival in the host country due to imperfect transferability of human capital across countries. Different scenarios could therefore explain the differences in returns to education. First, there may be increased uncertainty about the quality of education received by immigrants abroad, leading employers to hedge against the possibility of lower quality education. Second, language barriers may reduce the value of education for similarly educated immigrants. Third, immigrants may experience different returns to education after arrival due to downgrading. Untapped immigrant human capital due to over-education (Green et al, 2007), and more generally educational mismatch (Aleksynska & Tritah, 2013; Chiswick & Miller, 2009; Akgüç & Parasnis, 2023), can hinder the economic and social integration of immigrants, and thus prevent host countries from taking full advantage of the productive potential of immigrants.

Our objective in this work is to investigate the process of immigrant assimilation before and after the Great Recession across countries in Western Europe. Relative to previous work on immigrants' assimilation, and particularly the work of Lee et al. (2022), our analysis has the novelty of investigating assimilation in terms of educational mismatch, by confronting immigrants and natives along this dimension, and revealing cross-country and gender heterogeneity. Indeed, institutional differences across European countries in the form of integration policies as well as labour market policies may prevent or, on the contrary, boost the process of convergence between natives and immigrants. Therefore, we also relate estimated country measures of convergence in terms of educational mismatch to macroeconomic and socio-cultural factors in the host countries. Our objective is to identify which countries are most inclusive and under which circumstances immigration assimilation is most effective.

Our results suggest that between 1999 and 2008, upon arrival, migrant women were 8.8 percentage points more likely to experience educational mismatch than native women, while for men the same gap was 6.8 percentage points. These are huge differences between migrants and natives and point to substantial initial difficulties in integrating into the labour market. In the post-recession period, the gap was somewhat lower for men than in the earlier period, but it was even larger for woman (equal to 9.5 percentage points). The most striking result of our analysis is that the gap between migrants and natives widens over the first few years after arrival, and starts to narrow only after several years of residence in the host country. This points to long-lasting difficulties for migrants in finding adequate employment in the host country. Analysis of the pooled country sample reveals important heterogeneity across countries when gap estimates are disaggregated by country. There are notable differences across countries, depending on the time period and gender examined. Overall, there is a robust negative correlation between the initial gap and the convergence coefficient. This highlights the importance of the conditions upon arrival, and means that large initial migrant-native gaps persist for a long time and feed into slow assimilation of migrants afterwards.

The remainder of the paper is organized as follows: section 2 presents the data and the empirical methodology. Section 3 provides the main results and section 4 concludes.

2 Data and empirical methodology

2.1 Data

The primary data source for this analysis is the European Union Labour Force Survey (EU-LFS). The EU-LFS is a cross-sectional household survey carried out by each member state to collect information on labour force participation of people aged 15 and above. This survey has the advantage of a large sample coverage over a long time span and of collecting a wide range of socio-demographic characteristics and job attributes.

We restrict our sample to 14 countries from Western Europe for which data are available over the whole period of investigation 1999-2018.[1] We divide the data into two distinct periods: the first covers the pre-recession years from 1999 to 2008, and the second covers the post-recession years from 2009 to 2018. We draw information from the EU-LFS on each individual's country of birth to define their migration status. We define immigrants in our sample as "foreign-born" as opposed to "natives" who are born in the reporting country. We also define different migrant cohorts based on the length of the stay of each immigrant and taking into account the

[1] The countries covered are Belgium (BE), Denmark (DK), France (FR), Germany (DE), Greece (EL), Ireland (IE), Italy (IT), Netherlands (NL), Portugal (PT), Spain (ES) and the United Kingdom (UK), Finland (FI), Sweden (SE) and Austria (AT). We exclude Luxembourg because of too small a sample size.

survey year. This variable is important to account for any unobserved differences between immigrant cohorts. We further restrict our sample by including immigrants who arrived in the host country at the age of 18 or older but at the time of the survey were between 25 to 75 years old to avoid including people who were in the process of initial labour market transition. Indeed, labour market entrants, whether they are natives or immigrants, are more prone to temporary educational mismatch. We focus our analysis on immigrant assimilation over a 10-year period as in Lee et al. (2022) by considering immigrants with a maximum stay of 10 years. Tables 1 and 2 report the sample size for each cohort for the first period (1999-2008) and the second period (2009-2018), respectively. Our sample includes 17,071,837 individuals from 14 countries.

Table 1: Size of individual cohorts in Period 1 (1999-2008)

	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	Total
Natives											
	446 126	448 730	471 760	479 579	452 417	512 734	1 454 116	912 328	985 383	983 279	7 146 452
Cohorts											
1999		824	945	1 114	1 222	1 485	5 345	3 443	2 905	3 619	20 902
2000			993	1 062	1 431	1 689	5 759	4 321	4 809	4 259	24 323
2001				1 210	1 322	1 584	5 617	4 420	5 277	5 708	25 138
2002					1 083	1 238	4 624	3 570	5 246	4 927	20 688
2003						1 022	3 449	3 160	3 999	4 389	16 019
2004							2 657	2 611	3 873	4 306	13 447
2005								2 263	4 154	4 604	11 021
2006									4 250	4 777	9 027
2007										3 329	3 329
Total	446 126	449 554	473 698	482 965	457 475	519 752	1 481 567	936 116	1 019 896	1 023 197	7 290 346

Table 2: Size of individual cohorts in Period 2 (2009-2018)

	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Total
Natives											
	928 574	944 594	907 040	1 046 333	1 000 394	992 534	973 386	970 018	948 142	906 596	9 617 611
Cohorts											
2009		1 678	2 570	3 591	3 748	4 203	4 356	4 391	3 859	3 470	31 866
2010			1 919	3 284	3 533	4 062	4 318	4 461	4 412	3 553	29 542
2011				2 240	3 041	3 571	4 251	4 371	4 332	4 128	25 934
2012					2 238	3 417	4 001	4 145	4 375	4 160	22 336
2013						2 599	3 723	4 235	4 635	4 523	19 715
2014							2 565	3 738	4 546	4 994	15 843
2015								2 445	3 823	4 429	10 697
2016									2 236	3 503	5 739
2017										2 208	2 208
Total	928 574	946 272	911 529	1 055 448	1 012 954	1 010 386	996 600	997 804	980 360	941 564	9 781 491

Our central variable of interest is educational mismatch, which we measure using the realised-matches procedure (Chiswik & Miller, 2010, Aleksynska & Tritah, 2013). For each occupation, we first derive the mean and standard deviation of educational attainment. All individuals with a level of educational attainment which is at least one and a half standard deviations away from the mean are then considered "mismatched", either because they are undereducated (below the mean) or overeducated (above the mean). Occupations are identified according to the International Standard Classification of Occupations (ISCO) at the 2-digit level. Educational attainment is measured by the highest ISCED[2] level attained by a worker at the time of the survey. Education, therefore, refers to the formal qualifications obtained at a specific point in time. These credentials are likely to differ between countries, despite a harmonised system of educational equivalence in Europe. Similarly, the qualifications acquired in the starting period of our sample (1999) may be different from those acquired in later years (2018). Furthermore, in the current context of no formal equivalence between qualifications obtained inside and outside Europe, there are differences in the qualifications of natives and immigrants. The solution adopted to deal with these differences is to make the occupational benchmark time- and country-specific and to consider only native workers for the benchmark calculation.

Table 3: Incidence of mismatch (in %) by gender in the 1st Period (1999-2008) and in the 2nd Period (2009-2018)

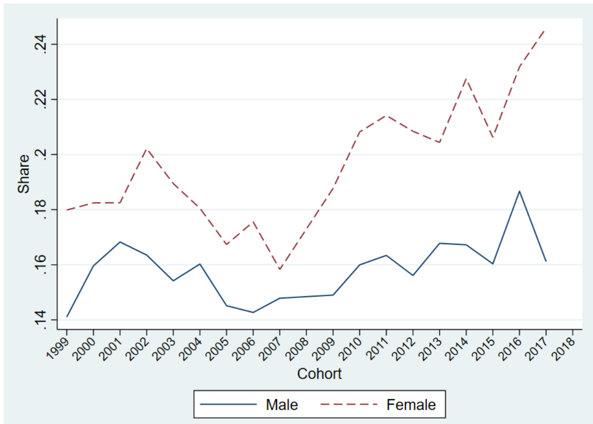
	All, Period 1	Male, Period 1	Female, Period 1	All, Period 2	Male, Period 2	Female, Period 2
Natives						
Education mismatch	12.58	12.94	12.12	12.73	13.16	12.22
Overeducation	7.04	7.24	6.80	6.84	6.72	6.97
Undereducation	5.53	5.70	5.32	5.89	6.45	5.25
Migrants						
Education mismatch	23.32	22.75	24.04	28.29	28.32	28.26
Overeducation	16.81	15.58	18.35	18.15	16.08	20.73
Undereducation	6.51	7.17	5.68	10.15	12.25	7.53

[2] ISCED refers to the International Standard Classification of Education. This classification was revised in 2011 with changes in the breakdown of education programmes implemented from the reference year 2014.To overcome the changes in ISCED categories, we aggregate educational attainment to the 1-digit level and convert the newest version of ISCED (ISCED2011) to the oldest version (ISCO97) using the correspondence tables from Eurostat. Our final variable of education then has 7 levels corresponding to: ISCED 0 (Pre-primary education), ISCED 1 (Primary education or first stage of basic education), ISCED 2 (Lower secondary education), ISCED 3 (Upper secondary education), ISCED 4 (Post-secondary non-tertiary education), ISCED 5 (First stage of tertiary education), ISCED 6 (Second stage of tertiary education).

The gap between migrants and natives in terms of educational mismatch is clearly visible from the data in Table 3. It shows the shares of educationally mismatched individuals among natives and migrants disaggregated by gender and the two time periods covered in the analysis. The reported statistics are weighted using the yearly weighting factor provided in the EU-LFS. The incidence of education mismatch is substantially higher for migrants than for natives for every form of mismatch. More strikingly, the proportion of overeducated migrants is more than twice as high as the proportion of overeducated natives. The likelihood for migrant women to be mismatched is three times higher than for native women. In the second period, the share of overeducated women was 6.7% for natives and 20.7% for migrants. The incidence of educational mismatch (over time) reveals other significant differences between migrants and natives. Over the two periods considered, the average incidence among natives is relatively stable at around 13% in both periods. In contrast, the incidence of mismatch for migrants increases from 23% in the first period to 28% in the second period. There are also marked differences between migrant cohorts, as depicted in Figures 1 and 2. The prevalence of educational mismatch is higher among migrant cohorts following the financial crisis, with a similar pattern observed for overeducation. The gender gap is more pronounced for overeducation, with a difference of 2 percentage points between men and women for the cohorts that arrived in 1999 and 8 percentage points for those that arrived in 2017.

Figure 1: Extent of educational mismatch by arrival cohort

Figure 2: Extent of overeducation by arrival cohort



Note: The figures plot the shares of individuals who are educationally mismatched and overeducated, by arrival cohorts.

2.2 Empirical strategy

Our empirical investigation aims to analyse immigrant assimilation in each country by focusing on our measure of educational mismatch. The observed differences between migrants and natives, as well as between men and women, are expected to lead to different assimilation patterns, which we aim to investigate using the following equation:

$$Y_i = \beta_0 + \beta_1 Migration\ Status_i + \beta_2 Z_i + \beta_3 Z_i^2 + \beta_4 Z_i^3 + \gamma X_i + \varepsilon_i \quad (1)$$

In this equation, Y is a binary variable equal to 1 if the individual is educationally mismatched and 0 otherwise, $Migration\ Status$ is a binary variable for migrants which is equal to one if the individual is foreign-born, and zero otherwise, and Z is equal to the years since migration, bounded between 0 for natives and higher values for immigrants with a maximum of 10-years of residence in the host country. X is a matrix of control variables including marital status, 2-digit occupations, employment status, work experience, and age.[3] Fixed effects for years and regions are included in all the regressions.

We estimate this equation using Linear Probability Models separately for men and women in each country and for each of the two periods considered (1999-2008 and 2009-2018). From this first estimation, we quantify the gap between natives and immigrants regarding educational mismatch. This gap is given by the coefficient β_1. It is expected to be positive, meaning that immigrants are more likely to be educationally mismatched than their native counterparts. The coefficient of *ysm* (years since migration) is expected to be negative as immigrants are expected to reach a better recognition of their qualification as time passes, and then have a better match of their educational attainment and the qualifications required in their occupation. The coefficients of the squared and cubic terms on years since migration capture the assimilation path over different time horizons.

We also estimate an alternative equation where instead of migration status, which provides an average gap for all immigrants relative to natives, we introduce a cohort variable in the regression:

$$Y_i = \beta_0 + \beta_1 Cohort_i + \beta_2 Z_i + \beta_3 Z_i^2 + \beta_4 Z_i^3 + \gamma X_i + \varepsilon_i \quad (2)$$

[3] Table 1 in the appendix presents descriptive statistics for all variables, broken down by gender and time period.

The $Cohort$ variable is a dummy variable for a specific cohort defined by the year of arrival in the host country. The benchmark category are the natives. The objective is to capture the gap between the foreign-born who immigrate to the host country in a specific year and the natives, that is, we estimate cohort-specific gaps between migrants and natives. Differences across cohorts may arise because of factors related to the specific context of the host countries as well as the origin countries. Among the factors influencing the various cohorts are education policies that could be especially important for specific generations.

3 Results

3.1 Average initial gap of educational mismatch

We start our analysis by examining the average gap between natives and migrants in terms of educational mismatch. The results presented in Table 4 are derived from estimating equation (1) by gender and time period across all countries in our sample[4]. The average difference, in the year of arrival, between migrants and natives regarding the probability of being educationally mismatched is given by the coefficient of the variable $Migration\, Status$ in equation (1), henceforth referred to as the average initial gap. As expected, both male and female immigrants are more likely to experience educational mismatch than natives. However, the difference is more pronounced for women, with a disadvantage of 8.8 percentage points in the first period compared to a difference of 6.8 percentage points for men. Interestingly, while the initial gap seems to narrow somewhat for men in the second period, it widens for women, from 8.8 percentage points in the first period to 9.5 percentage points in the second period.

Table 4: Estimates of initial gap by gender and time period for all countries

	Female, Period 1	Male, Period 1	Female, Period 2	Male, Period 2
Migration Status	0.088***	0.068*	0.095***	0.052*
	(0.026)	(0.028)	(0.021)	(0.024)
Years of residence	0.025	0.020	0.037*	0.057***
	(0.020)	(0.020)	(0.017)	(0.016)
Years of residence squared	-0.004	-0.003	-0.009*	-0.011**
	(0.005)	(0.005)	(0.004)	(0.004)
Years of residence cubed	0.000	0.000	0.001*	0.001*
	(0.000)	(0.000)	(0.000)	(0.000)

Note: Standard errors in parentheses. * $p<0.05$, ** $p<0.01$, *** $p<0.001$. The dependant variable is individual education mismatch taking the value of 1 if the individual is mismatched and 0 otherwise. All regressions include control variables (age, marital and employment status, work experience) and the full set of survey, occupation, country and regions fixed effects. The estimations are weighted using the survey weights provided by Eurostat and the errors are clustered at the regional level.

[4] Table 2 in the Appendix displays the regression results with all the control variables.

Looking at the convergence after one year in the host country, the gap in the probability of educational mismatch between immigrants and natives actually increases by 2.1%-points (0.025+(-0.004)+0.000) for women and by 1.7%-points for men in the first period. The match quality, therefore, deteriorates for immigrants one year after their arrival. This effect is even more pronounced in the second period, especially for men. Indeed, the gap in the probability of education mismatch increases by 4.7 percentage points among migrant men after one year of residence, while the same number for women is 2.9 percentage points. We can assume that it takes more than one year of residence in the host country to acquire the language skills and labour market knowledge needed to find a job that matches one's educational level. We can underline this hypothesis by calculating the convergence after a decade of residency by multiplying the coefficients of years of residence, years of residence squared, and years of residence cubed by 10^1=10, 10^2=100, and 10^3=1000, respectively. The resulting coefficient indicates the convergence between immigrants and natives regarding the probability of educational mismatch over a 10-year period. For instance, the 10-year convergence coefficient for women during the first period amounts to -15% (10*0.025+100*(-0.004)+1000*0.000), indicating a 15 percentage point decrease in the probability of educational mismatch for immigrant women. Adding the 10-year convergence coefficient to the initial gap provides the 10-year gap. Accordingly, the 10-year gap for women in the first period is given by 0.088-0.15=-0.062, indicating that after a decade the probability of educational mismatch for migrant women is 6.2 percentage points lower than that for native women. Similarly, the 10-year gap for men is in favour of migrants with a mismatch probability of 3.2 percentage points less than natives. However, the scenario changes dramatically in the post-recession period. Starting from an initial gap of 9.5 and 5.2 percentage points for women and men respectively, the gap widens to 56 and 52 percentage points for women and men respectively.

Instead of an average initial gap between immigrants, Table 5 highlights the differences between cohort estimates from equation (2) by gender and by time period for the pooled sample of European countries.The variable cohort is measured by the immigrant's year of arrival in each European country and takes the value 0 for natives. The coefficients reported in Table 5 are the percentage point differences in the probability of being mismatched for a given cohort compared to natives. In line with the previous results in Table 4, all immigrant cohorts have a higher probability of being educationally mismatched. However, the size of the gap varies between the cohorts and between men and women. The probability of education mismatch is overall higher for the cohorts that immigrated in the first period compared to the period from 2009-2018, probably due to more targeted migration policies. The female cohorts are more disadvantaged than the male cohorts, with an initial gap that is often higher than 10%. This is particularly the case for the cohorts that arrived before 2003 and after 2015. The maximum gap (around 9%) for men is found for the cohorts arriving in 1999 and 2000, but for the following cohorts the gap narrows.

Table 5: Estimates of cohorts' initial gaps by gender and time period for all countries

	Female, Period 1	Male, Period 1	Female, Period 2	Male, Period 2
1999	0.120***	0.092**		
	(0.032)	(0.034)		
2000	0.108***	0.090*		
	(0.031)	(0.035)		
2001	0.104**	0.096**		
	(0.033)	(0.033)		
2002	0.128***	0.079*		
	(0.029)	(0.032)		
2003	0.098***	0.089**		
	(0.029)	(0.027)		
2004	0.103***	0.064*		
	(0.028)	(0.025)		
2005	0.074*	0.042		
	(0.029)	(0.029)		
2006	0.078***	0.056*		
	(0.023)	(0.024)		
2007	0.093**	0.066		
	(0.035)	(0.040)		
2009			0.068***	0.053**
			(0.020)	(0.019)
2010			0.090***	0.047*
			(0.018)	(0.023)
2011			0.091***	0.044
			(0.022)	(0.024)
2012			0.096***	0.048
			(0.021)	(0.027)
2013			0.082***	0.069*
			(0.019)	(0.027)
2014			0.092***	0.067**
			(0.020)	(0.024)
2015			0.050	0.037
			(0.028)	(0.031)
2016			0.107***	0.047
			(0.026)	(0.032)
2017			0.107***	0.086***
			(0.030)	(0.025)
Years of residence	0.019	0.019	0.048**	0.055***
	(0.019)	(0.019)	(0.015)	(0.016)
Years of residence squared	-0.004	-0.005	-0.012***	-0.011**
	(0.004)	(0.004)	(0.003)	(0.004)
Years of residence cubed	0.000	0.000	0.001***	0.001*
	(0.000)	(0.000)	(0.000)	(0.000)

Note: Standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. The dependant variable is individual education mismatch (category) taking the value of 1 if the individual is mismatched and 0 otherwise. All regressions include control variables (age, marital, work experience and employment status) and the full set of survey, occupation, country and regions fixed effects. The estimations are weighted using the survey weights provided by Eurostat and the errors are clustered at the regional level.

3.2 Country-specific estimates of initial gap

As a next step, we replicate our previous estimates of the migrant-native educational mismatch gap for each European country. Table 6 reports the estimates of initial gap, convergence coefficient and the 10-year gap from equation (1) estimated separately for each gender, period, and country[5]. The initial gap is positive for almost all European countries. However, there exists notable heterogeneity as the magnitude of this gap varies significantly among countries and genders, with some exhibiting a markedly larger difference between migrants and natives. In the 1st period, women in Denmark, France, and Portugal exhibit the highest initial gap coefficients, with values of 0.355, 0.246, and 0.222, respectively. Remarkably, these disparities diminish in these countries during the post-recession period. Conversely, in certain countries, the initial gap widens notably for women in the later period. For instance, the initial gap increased by 10 percentage points in Germany and by 30 percentage points in Sweden. Additionally, significant increases in the initial gap are observed for male individuals across the two periods. Notably, Denmark experiences a substantial 48.2 percentage point rise, transitioning from -0.223 in the first period to 0.259 in the second period. In contrast, Greece observes a comparatively moderate increase of 16.6 percentage points, while Spain and the Netherlands register increases of 10 and 5 percentage points, respectively. Similarly, Sweden experiences a marginal rise of approximately 4.7 percentage points over the specified periods.

[5] The corresponding regressions for each country, including all the control variables, are available on request from the authors.

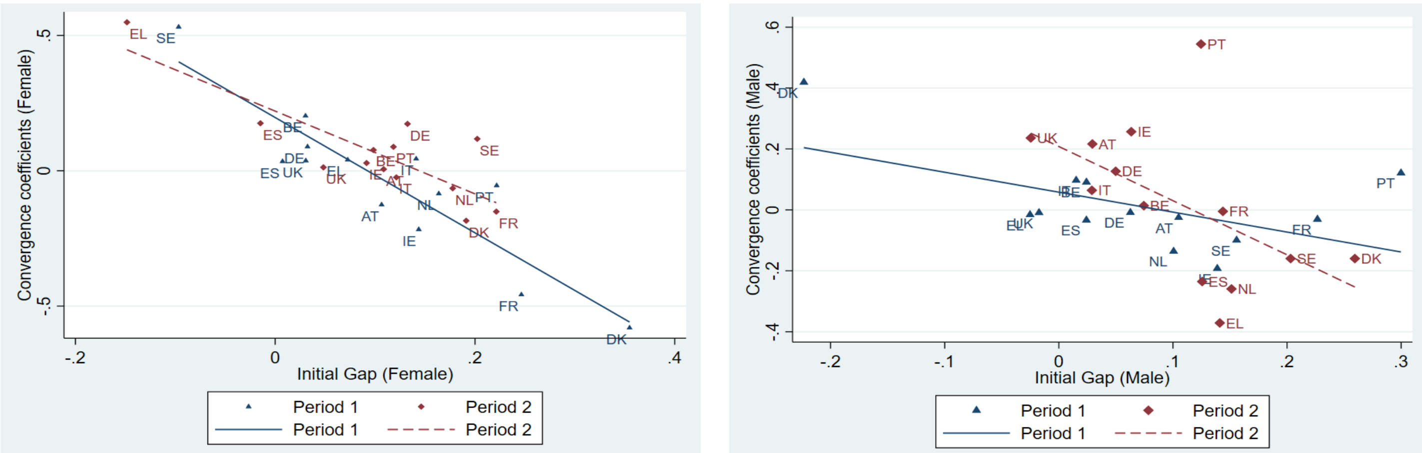
Table 6 : Education mismatch probability estimates

		Female, Period 1	Female, Period 2	Male, Period 1	Male, Period 2
AT	Initial Gap	0.107	0.109	0.105	0.029
	Convergence	-0.125	0.006	-0.025	0.216
	10-year Gap	-0.019	0.115	0.08	0.246
BE	Initial Gap	0.03	0.098	0.024	0.075
	Convergence	0.203	0.077	0.091	0.014
	10-year Gap	0.233	0.175	0.115	0.088
DE	Initial Gap	0.032	0.132	0.063	0.05
	Convergence	0.089	0.173	-0.009	0.127
	10-year Gap	0.121	0.306	0.054	0.177
DK	Initial Gap	0.355	0.191	-0.223	0.259
	Convergence	-0.58	-0.184	0.419	-0.16
	10-year Gap	-0.225	0.007	0.195	0.1
EL	Initial Gap	0.073	-0.148	-0.025	0.141
	Convergence	0.04	0.549	-0.016	-0.371
	10-year Gap	0.113	0.4	-0.041	-0.23
ES	Initial Gap	0.007	-0.015	0.024	0.126
	Convergence	0.035	0.176	-0.034	-0.235
	10-year Gap	0.042	0.161	-0.009	-0.109
FI	Initial Gap	-1.241	-0.379	-0.48	-0.027
	Convergence	2.479	0.71	0.614	-0.351
	10-year Gap	1.238	0.332	0.134	-0.378
FR	Initial Gap	0.246	0.221	0.227	0.144
	Convergence	-0.458	-0.151	-0.031	-0.005
	10-year Gap	-0.211	0.071	0.196	0.139
IE	Initial Gap	0.144	0.091	0.139	0.063
	Convergence	-0.217	0.029	-0.192	0.257
	10-year Gap	-0.073	0.12	-0.053	0.32
IT	Initial Gap	0.141	0.121	0.015	0.029
	Convergence	0.044	-0.024	0.097	0.064
	10-year Gap	0.185	0.097	0.112	0.093
NL	Initial Gap	0.164	0.178	0.101	0.151
	Convergence	-0.085	-0.065	-0.136	-0.259
	10-year Gap	0.079	0.113	-0.035	-0.108
PT	Initial Gap	0.222	0.118	0.3	0.125
	Convergence	-0.055	0.089	0.121	0.544
	10-year Gap	0.167	0.207	0.421	0.669
SE	Initial Gap	-0.097	0.202	0.156	0.203
	Convergence	0.531	0.118	-0.1	-0.16
	10-year Gap	0.435	0.32	0.056	0.043
UK	Initial Gap	0.031	0.048	-0.017	-0.025
	Convergence	0.037	0.013	-0.009	0.236
	10-year Gap	0.068	0.061	-0.026	0.212

Looking at the convergence coefficients, and the gap after 10 years, significant cross-country disparities become evident.. Indeed, only a handful of countries exhibit a decrease in the probability of education mismatch for migrants compared to natives. The coefficient on convergence is negative for some countries, denoting a decrease in the probability of education mismatch for migrants relative to natives. A positive coefficient would suggest a widening gap. In the 1st period, the gap narrows for women in Austria, Denmark, France, Ireland, Netherlands and Portugal and for men in Austria, Germany, Spain, France, Ireland, Netherlands and Sweden. However, in the 2nd period, the convergence coefficient is positive for migrant women in nearly all European countries, indicating a deterioration in the alignment between immigrant women's education and their jobs compared with natives.

Figure 3 shows the relationship between the initial gap and the convergence coefficient by gender in both periods and in each country. There is a strong negative association between the initial gap and the convergence for men and women in both periods.

Figure 3: Link between initial gap and 10-year gap



3.3 Education mismatch gap, macroeconomic context and social attitudes

The results outlined in the previous section highlight considerable heterogeneity across countries regarding the estimated gap of educational mismatch between migrants and natives both before and after the Great Recession. This heterogeneity can be attributed to country-specific factors that either foster or impede the assimilation of migrants. Determinants include a range of influences, from differences in institutional frameworks and labour market dynamics to variations in immigration policies and socio-cultural contexts. In this section, we will examine the roles of macroeconomic conditions and social attitudes towards immigrants, since these factors have already been established in the literature as likely to shape immigrants' assimilation.

First, in macroeconomic contexts characterized by diminished job prospects and economic volatility, migrants may find themselves compelled to accept employment roles that do not correspond to their educational attainment or skill set. In such scenarios, the labour market options available to migrants may be restricted, prompting them to compromise on the appropriateness of job placements in favour of attaining financial security and stability. Migrants may therefore experience underemployment or work in jobs that do not fully require them to utilize their education or professional skills (Bratsberg et al. 2006, Dustmann et al. 2010).

Secondly, socio-cultural factors and attitudes towards migrants may play a key role in shaping the process of migrant assimilation within the host societies. These factors include societal attitudes, norms, and cultural practices that affect how migrants are perceived, received, and integrated into their new environment. Positive attitudes can help migrants assimilate more quickly, by creating a welcoming environment that encourages their participation in social, economic, and cultural life. Negative attitudes, such as xenophobia, prejudice, and discrimination, hinder integration and impede migrants' access to opportunities, obstructing their social inclusion.

We introduce a host of variables that are meant to capture these macro conditions and attitudes towards migrants. As it turns out, the only significant factor is related to economic growth, with a positive coefficient indicating lower assimilation of migrants even in a favourable economic context. The other macroeconomic variables and the attitudinal indicators do not show a significant correlation with the convergence coefficient. A possible explanation is the small number of observations and the averaging of macroeconomic variables over the two periods.

Table 7 : Potential factors contributing to varying convergence estimates

	Female	Male	all
Average GDP growth	-0.012	0.043*	0.020
	(0.009)	(0.016)	(0.013)
Unemployment rate	0.002	-0.010	-0.002
	(0.005)	(0.009)	(0.005)
Different race/ethnic of relatives partner	0.589	-0.185	0.324
	(0.412)	(0.420)	(0.358)
Different race/ethnic of boss	0.480	-0.280	0.302
	(0.435)	(0.456)	(0.315)
Law against ethnic discrimination in workplace	-0.370	0.189	-0.210
	(0.459)	(0.723)	(0.654)
Shared customs and traditions	-0.729	0.383	-0.269
	(1.146)	(1.688)	(1.578)
Job creation by migrants	-0.444	0.285	-0.187
	(0.516)	(0.519)	(0.485)
Crime problems by migrants	-0.056	-0.227	-0.349
	(0.408)	(0.430)	(0.369)
Generosity on judging applications for refugee status	-0.013	0.519	0.403
	(0.192)	(0.369)	(0.252)
Non necessity to speak country's official language	0.385	-0.380	0.157
	(0.294)	(0.241)	(0.279)

Note: The dependant variable is the 10-year convergence coefficient estimated by gender for each period and country. The coefficients reported in this table stem from distinct regressions of gender-specific convergence coefficients on each macroeconomic and socio-cultural factor while controlling for the initial gap. Robust standard errors clustered at the country level are reported in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

4 Conclusions

This paper provides empirical evidence regarding the differences and convergence dynamics between migrants and natives in terms of educational mismatch across Western European countries. Gender-specific analyses uncover remarkable patterns in the labour market assimilation process. Both male and female migrants face a strikingly higher probability of educational mismatch compared to natives. Women in particular experience a more pronounced disadvantage, characterised by a significant difference in the probability of educational mismatch. Interestingly, the initial gap for both men and women widens in the first few years after arrival, indicating a persistent challenge in labour market integration. Our research thus highlights the long adjustment period required for immigrants to close the gap with natives. In addition, our analysis extends to cohort estimates, revealing different degrees of disadvantage across immigrant cohorts and genders. In particular, cohorts arriving before 2003 and after 2015, and especially female migrants, face greater challenges in terms of educational mismatch.

From a cross-country perspective, there is a significant initial gap between migrants and natives in terms of educational mismatch in almost all countries. However, the size of this gap varies considerably across countries. More research is needed to get a better understanding of the exact determinants of these differences.

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APPENDIX

Table 1 : Descriptive statistics of the core variables

	Male, Period 1	Female, Period 1	Male, Period 2	Female, Period 2	Total
Foreign-born	1.87%	1.87%	1.68%	1.56%	1.73%
Natives					
Education mismatch	12.94%	12.12%	13.16%	12.22%	12.66%
Overeducation	7.24%	6.80%	6.72%	6.97%	6.92%
Undereducation	5.70%	5.32%	6.45%	5.25%	5.74%
Employment rate	96.54%	95.81%	93.98%	94.40%	95.04%
Married	65.76%	63.18%	59.81%	58.62%	61.53%
Age	43.46	42.46	45.43	44.71	44.21
Work experience	23.65	21.67	24.56	22.68	23.32
Migrants					
Education mismatch	22.75%	24.04%	28.32%	28.26%	26.01%
Overeducation	15.58%	18.35%	16.08%	20.73%	17.53%
Undereducation	7.17%	5.68%	12.25%	7.53%	8.47%
Employment rate	92.86%	91.26%	89.34%	88.90%	90.53%
Married	61.78%	57.32%	56.70%	52.25%	57.06%
Age	36.09	36.22	36.76	37.1	36.56
Work experience	16.08	15.49	15.28	15.04	15.47
Years of residence	4.21	4.35	3.93	4.16	4.14

Table 2 : Education mismatch regressions

	Female, Period 1	Male, Period 1	Female, Period 2	Male, Period 2
Migration Status	0.083**	0.065*	0.093***	0.062**
	(0.026)	(0.029)	(0.023)	(0.022)
Years of residence	0.024	0.011	0.030	0.042*
	(0.019)	(0.021)	(0.019)	(0.019)
Years of residence squared	-0.005	-0.002	-0.008	-0.009*
	(0.004)	(0.005)	(0.004)	(0.004)
Years of residence cubed	0.000	0.000	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.000)
Work experience	-0.004***	-0.007***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Married (ref : Not married)	-0.007***	-0.005**	-0.008***	-0.005***
	(0.001)	(0.002)	(0.001)	(0.001)
Unemployed (ref. :employed)	0.008*	-0.006	0.011***	0.010**
	(0.003)	(0.003)	(0.002)	(0.003)
Age (ref : 25-29)				
30-34	0.008*	0.029***	0.001	0.013***
	(0.004)	(0.005)	(0.003)	(0.003)
35-39	0.011	0.056***	0.012**	0.027***
	(0.006)	(0.008)	(0.004)	(0.005)
40-44	0.024**	0.083***	0.017**	0.041***
	(0.008)	(0.012)	(0.006)	(0.007)
45-49	0.046***	0.117***	0.025**	0.052***
	(0.010)	(0.017)	(0.008)	(0.008)
50-54	0.083***	0.167***	0.043***	0.073***
	(0.012)	(0.020)	(0.010)	(0.011)
55-59	0.116***	0.210***	0.077***	0.100***
	(0.016)	(0.023)	(0.013)	(0.013)
60-64	0.134***	0.246***	0.112***	0.132***
	(0.018)	(0.028)	(0.016)	(0.016)
65-69	0.191***	0.307***	0.157***	0.184***
	(0.022)	(0.033)	(0.021)	(0.020)
70-74	0.217***	0.341***	0.199***	0.218***
	(0.026)	(0.037)	(0.027)	(0.025)
r2	0.029	0.033	0.025	0.020
N	2.35e+06	2.98e+06	4.15e+06	4.80e+06

Table 3: Data description

Source	Variable	Description
Eurostat	Average GDP growth Unemployment rate	Annual values averaged over each period
European Social Survey (ESS)	Different race/ethnic of relatives partner Different race/ethnic of boss	0-10 scale response to the questions, "How much would you mind if people from another country who are of a different race married to a close relative of yours/is your boss?" is inversely rescaled to 0-1 scale and averaged by country.
	Law against ethnic discrimination in workplace Shared customs and traditions Job creation by migrants Crime problems by migrants	0-10 scale response to the questions, "How good is it for a country to have a law against racial or ethnic discrimination in the workplace?", "How much would you agree that it is better for a country if almost everyone shares the same customs and traditions?", "Would you say that people who come to live here generally help to create new jobs?", "Are host country's crime problems made better by people coming to live here from other countries?" is inversely rescaled to 0-1 and averaged by country.
	Generosity on judging apps for refugee status	Categorical response to the statement, "Governments should be generous when judging applications for refugee status.". is inversely recoded to 0-1 scale numeric variable (Strongly Agree = 1, Agree = 0.66, Disagree = 0.33, Strongly Disagree = 0) and then averaged by country.
	Non necessity to speak country's official language	0-10 scale response to the question, "How important should it be for migrants to be able to speak host country's official language?", is inversely rescaled to 0-1 by dividing the value by 10 and then averaged by country.

GI-NI PROJECT IDENTITY

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Growing Inequality: a novel integration of transformations research — GI-NI

Coordinator

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Consortium

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Centre for European Policy Studies (Belgium)
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