# Which Degree for Which Occupation? Vertical and Horizontal Mismatch Among Immigrants, Their Children, and Grandchildren in France 

Rosa Weber, Mathieu Ferry et Mathieu Ichou

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## POUR CITER CETTE VERSION / TO CITE THIS VERSION

Rosa Weber, Mathieu Ferry et Mathieu Ichou, 2023, "Which Degree for Which Occupation? Vertical and Horizontal Mismatch Among Immigrants, Their Children, and Grandchildren in France". Documents de travail, $\mathrm{n}^{\circ} 278$, Aubervilliers : Ined.

Disponible sur / Availabe at:
http://hdl.handle.net/20.500.12204/E5OPhosBhU4QGwadVTE1

# DOCUMENTS278 

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## Novembre 2023

## Which Degree for Which Occupation?

Vertical and Horizontal Mismatch Among Immigrants, Their Children, and Grandchildren in France

Rosa Weber ${ }^{1,2}$ Mathieu Ferry ${ }^{1,3}$ Mathieu Ichou ${ }^{1}$<br>${ }^{1}$ Institut National d'Études Démographiques, 93300 Paris, France<br>${ }^{2}$ Stockholm University, Department of Sociology, 10691 Stockholm, Sweden<br>${ }^{3}$ Laboratoire Printemps, Université de Versailles Saint-Quentin-en-Yvelines, 78280 Guyancourt, France


#### Abstract

Prior research shows that immigrants are often over-educated: their educational attainment is higher than what is required or commonly observed in their occupation. Yet, less is known about the education-occupation mismatch among immigrants' children and grandchildren (the second and third generations). Using the French Trajectories and Origins 2 (TeO2, 2019-2020) survey, we test theoretically-grounded hypotheses on the level of and mechanisms underlying vertical (educational attainment) and horizontal (field of study) mismatch in the first, second, and third generations. Results indicate that vertical mismatch is substantially lower in the second and third generations than in the first, giving credence to the hypothesis that vertical mismatch is largely the result of imperfect international transferability of credentials. By contrast, higher levels of horizontal mismatch persist in the second and third generations among men of non-European descent. Differences in horizontal mismatch between immigrants' and natives' descendants are largely accounted for by initial sorting into fields of study.


Keywords: education-occupation mismatch, immigrant integration, second generation, third generation, fields of study.

## Introduction

A rich body of research studies the education and labor market outcomes of immigrants and their descendants (Drouhot and Nee 2019; Heath et al. 2008). In many destination countries, children of immigrants, the so-called second generation, tend to have similar levels of educational attainment as natives, once differences in parental background are taken into consideration (Algan et al. 2010; Dustmann et al. 2012; Hermansen 2016). ${ }^{1}$ By contrast, differences in employment and earnings persist for some origin groups in certain destination countries (Algan et al. 2010; Platt and Nandi 2020), such as among the descendants of immigrants from North Africa in France (Meurs 2018; Meurs and Pailhé 2010; Primon et al. 2018). However, fewer studies have addressed the extent to which the educational qualifications attained by immigrants' descendants match their occupational position on the labor market.

Over-education is a common and consequential phenomenon in Europe (Quintini 2011), particularly among immigrants who are more often than natives over-qualified for their occupations (Andersson Joona et al. 2014; Visintin et al. 2015). Over-education has been connected to lower wages, accounting for a large share of the immigrant-native wage gap and explaining some of the wage disadvantages experienced by ethnoracial minorities (Andersson Joona et al. 2014; Lu and Li 2021). Wage penalties are especially high for immigrants who are both vertically and horizontally mismatched (Banerjee et al. 2019). Educational mismatch is further related to poorer self-rated health and lower psychosocial well-being, and especially so among immigrants (Dunlavy et al. 2016; Espinoza-Castro et al. 2019). Assessing the extent to which higher levels of educational mismatch persist among immigrants' children and grandchildren, as we do in this paper, sheds light on a major mechanism driving socioeconomic assimilation and ethnoracial inequalities.

Among immigrants, the commonly observed higher levels of educational mismatch have generally been interpreted as the result of the imperfect transferability of degrees and skills between the origin and destination countries (Aleksynska and Tritah 2013). Given that the descendants of immigrants are socialized and educated in the destination society, speak its language, and know its institutions, we would expect a decrease in educational mismatch across generations. Indeed, there are no a priori reasons why their educational degrees should be

[^0]differently valued on the labor market than natives'. However, racial discrimination and unequal reception contexts could also lead to persistently high levels of mismatch across generations, especially among members of racialized minority groups. To date, the small but growing literature on the education-occupation mismatch among the children of immigrants remains inconclusive. Some studies find limited evidence of mismatch in the second generation (Khoudja 2018; Pecoraro 2011), while others conclude that mismatch is actually strong, especially among the descendants of non-Western immigrants (Belfi et al. 2021; Dahlstedt 2015; Falcke et al. 2020).

Using the new French Trajectories and Origins 2 (TeO2, 2019-2020) survey, this study assesses the prevalence of educational mismatch across generations, regions of origin, and gender in France. We contribute to the literature in three ways. First, to our knowledge, ours is the first study to assess educational mismatch among the third generation, or immigrants' grandchildren. Prior studies have focused on first-generation immigrants (Andersson Joona et al. 2014; Visintin et al. 2015) and increasingly study the second generation (Belfi et al. 2021; Falcke et al. 2020; Khoudja 2018). However, we are not aware of any studies on the third generation, even though the demographic and social significance of this population group is increasing in established countries of immigration such as the US (Tran 2018) and France (Lê et al. 2022). Second, we jointly assess vertical and horizontal mismatch. There is a considerable literature on vertical mismatch, i.e., the level of divergence between individuals' educational attainment and their occupation. By contrast, less attention has been paid to horizontal mismatch, i.e., differences between individuals' field of study and their occupation. Third, we go beyond describing the extent of educational mismatch and test theoretically-grounded hypotheses on the mechanisms underlying observed mismatches. We distinguish between structural and individual mechanisms and assess whether they explain the observed differences between groups.

In the next sections, we review the relevant theories and previous literature on education-occupation mismatch among immigrants and their descendants, from which we draw our hypotheses. Then, we describe our data and methods and present our empirical findings. We conclude with a summary of our results and a consideration of their theoretical implications.

## Theoretical Background and Previous Literature

## Vertical and Horizontal Mismatch

Educational degrees-the level of attainment and field of study-are used as credentials to enter the labor market and as signals for employers. While specific credentials are strictly required for some so-called "closed occupations" (Weeden 2002), such as medical doctors and lawyers, most occupations are more open, resulting in within-occupation heterogeneity in workers' educational degrees.

Vertical mismatch is generally broken down into under-education (lower educational attainment than is required for or observed in a given occupation); over-education (higher educational attainment than is required for or observed in a given occupation); and no mismatch (similar educational attainment to what is required or observed) (Quintini 2011). Undereducation tends to increase with labor experience, as individuals are able to show their worth on the labor market and to progress within their company (Groot and Maasen van den Brink 2000; Insee 2021). In comparison, over-education is indicative of lower returns to individuals’ human capital investments and is generally linked to lower wages (Andersson Joona et al. 2014; Li and Lu 2023; Lu and Li 2021). Over-education can occur when too many applicants have the same level of education. In these situations, securing a job may entail having higher levels of educational attainment than required. Indeed, from this perspective, over-education is understood as an imbalance between labor supply and demand that results from a surplus of graduates compared to job openings.

Some recent work notwithstanding (Di Stasio 2017; Falcke et al. 2020; Li and Lu 2023), prior studies have paid less attention to horizontal mismatch. In certain situations, individuals can be expected to experience both vertical and horizontal mismatch at once. Indeed, individuals, who lack employment opportunities and whose career choices are constrained, are more likely to accept work that is both less qualified (vertical mismatch) and in a different field (horizontal mismatch) (Falcke et al. 2020). Similarly, over-education may compensate for a lack of occupation-specific training (Di Stasio 2017), which would result in both vertical and horizontal mismatch for individuals with unspecialized academic degrees.

Still, vertical and horizontal mismatch do not necessarily coincide, as they have distinct determinants. Higher levels of horizontal mismatch may be a sign of difficulties experienced in finding a job matching one's field of study. In this case, horizontal mismatch is said to be "demand-related" (Somers et al. 2019) because the job corresponding to the field of study is
not available or difficult to secure (Betts 1996). This type of horizontal mismatch is perceived as an undesirable outcome (Kucel and Vilalta-Bufí 2013). Indeed, the individuals concerned tend to earn lower salaries, as employers factor a "matching cost" (Bruyère and Lemistre 2005). However, there may be instances in which horizontal mismatch indicates a level of achievement. For instance, successful individuals may be headhunted into occupations outside of their field of study or get promoted to occupational positions outside of their initial training field, especially as they gain experience on the labor market (Somers et al. 2019). In a recent study, Li and Lu (2023) distinguish between horizontal undermatch-individuals who are employed in out-of-field occupations that pay less than matched occupations-and horizontal overmatch-individuals who are employed in out-of-field occupations that pay more than matched occupations. Their findings indicate that immigrants more often experience horizontal undermatch and less often horizontal overmatch than natives in the US.

## Educational Mismatch Among Immigrants and Their Descendants

Among first-generation immigrants, educational mismatch is a well-established empirical finding in Europe (Aleksynska and Tritah 2013) and in the US (Lu and Li 2021). Following human capital theory, imperfect international transferability of degrees and skills may account for over-education (Chiswick and Miller 2010) and horizontal mismatch among immigrants (Li and Lu 2023). Over-education has been deemed to be a form of "apparent" mismatch, given that skills could be poorly correlated to qualifications among newly arrived immigrants (Flisi et al. 2017; Prokic-Breuer and McManus 2016). For instance, language difficulties and limited institutional knowledge may increase the level of educational mismatch experienced among immigrants during the first years in the destination country. In line with this reasoning, educational mismatch has been shown to decrease as immigrants settle in the country (Banerjee et al. 2019; Larsen et al. 2018; Nielsen 2011), leading us to expect educational mismatch to have disappeared by the second generation.

Prior evidence on the educational mismatch of the descendants of immigrants is more limited. Studies suggest that the descendants of immigrants experience lower levels of mismatch than immigrants and sometimes even fully converge towards natives (Khoudja 2018; Pecoraro 2011), despite considerable differences across regions of origin (Belfi et al. 2021; Dahlstedt 2015; Falcke et al. 2020). For instance, children of non-Western immigrants are more likely to experience vertical mismatch than those from Western countries (Belfi et al. 2021; Dahlstedt 2015). Falcke et al. (2020) also find that Western and non-Western second-
generation graduates are more likely to experience horizontal mismatch than natives, while only non-Western groups are also more likely to experience vertical mismatch.

For immigrants and their descendants, educational mismatch-as it relates both to their educational and labor market incorporation-can be fruitfully conceived of through the lens of assimilation theories (Khoudja 2018). Assimilation theories lead us to competing expectations regarding educational mismatch among the descendants of immigrants. According to the neoclassical assimilation theory (Alba and Nee 2003) which reframes the classical assimilation theory (Park and Burgess 1921; Warner and Srole 1945), there is a gradual convergence between natives and immigrants' descendants as time and generations pass. Despite differences between the US and Western Europe and notable variations between groups, studies point to an overall pattern of intergenerational assimilation in terms of educational attainment and labor market outcomes (Drouhot and Nee 2019; Heath et al. 2008). As a result, the link between the degree obtained-characterized both by its level and field-and the occupation held should become increasingly similar to that of natives over generations. Considering educationoccupation mismatch as an additional indicator of socioeconomic incorporation, the neoclassical assimilation framework, as well as existing evidence lead us to expect a decline in both vertical and horizontal mismatch over generations among the children and grandchildren of immigrants.

However, there may also be differences in integration trajectories across ethnic groups. The segmented assimilation theory (Portes and Zhou 1993; Zhou and Gonzales 2019) and theories on exclusion (Telles and Ortiz 2008) assume that different ethnic groups follow distinct pathways and that immigrants' descendants may converge with natives in some areas but not in others (White and Glick 2009). The theories posit that the segmented character of assimilation is the result of an interaction between individuals' human capital, parental socioeconomic status, and the characteristics of the co-ethnic community, on the one hand, and the policies, values, and prejudice in the receiving society, on the other (Zhou and Gonzales 2019). For instance, negative beliefs against certain ethnic minorities can lead to discounting their skills (Esses et al. 2006). While the segmented assimilation theory originates from the US, previous studies suggest that it may also apply to the French setting (Safi 2006). In the US, mechanisms of marginalization are intertwined with the legacy of slavery and skin colorbased racism. In France, research underscores the impact of colonial history and ethnic discrimination as sources of segregating dynamics against certain immigrant-origin groups (Drouhot and Nee 2019; Silberman et al. 2007; Silberman and Fournier 2006). Overall, the descendants of non-European immigrants have lower socioeconomic outcomes and are more
at risk of being outside the labor market (Meurs 2018; Meurs and Pailhé 2010; Primon et al. 2018). This leads us to expect that the descendants of non-European immigrants are likely to experience more durable education-occupation mismatch than the descendants of European immigrants.

## Education-Occupation Mismatch as a Gendered Process

Men and women may experience different levels of educational mismatch, as gender differences in fields of study and occupations persist (G. B. Dahl et al. 2023; Humlum et al. 2019). Women continue to be overrepresented in the arts and humanities and in health, while men are overrepresented in STEM fields and occupations (Hermansen and Penner 2022). Recent work indicates heterogeneity in the gendered patterns of educational mismatch across educational groups and life stages, showing that college-educated women are more likely to experience educational mismatch than men (Addison et al. 2020).

The few prior studies that have assessed gender differences in the educational mismatch of immigrants provide heterogeneous findings (Birgier and Bar-Haim 2023; Pecoraro 2011). However, in general, ethnic minority men are often stereotyped as threatening and therefore more likely to experience discrimination than minority women (Sidanius and Pratto 2001). This pattern has been verified in hiring discrimination in Denmark (M. Dahl and Krog 2018) and Sweden (Arai et al. 2016). Wage disadvantages also appear greater for minority men in the US (Mandel and Semyonov 2016) and in France (Gueye and Ceci-Renaud 2022). Therefore, as they are more likely to experience discrimination on the labor market, male descendants of ethnic minority immigrants are expected to undergo higher education-occupation mismatch than women from the same ethnic group.

## Mechanisms Underlying Differences in Educational Mismatch

To gain a better understanding of what explains gaps in vertical and horizontal mismatch between natives, immigrants, and their descendants, we identify three structural and three individual mechanisms. Structural mechanisms-occupational closure, vocational training, and fields of study-refer to the structure of the educational system and labor market and, specifically, the allocation of individuals into distinct educational tracks and occupations. First, accessing so-called "closed occupations" requires holding a specific type of degree (Weeden 2002). Therefore, occupational closure almost guarantees the absence of any educational mismatch. These degrees often imply a considerable investment in human capital. For instance, obtaining a medicine degree takes $9-12$ years after high school in France. If immigrants and
their descendants are underrepresented in these low-mismatch occupations (Lancee and Bol 2017), this could contribute to explaining higher levels of mismatch in these groups.

The second mechanism concerns vocational training, which provides individuals with occupation-specific skills. Prior research finds that individuals with vocational degrees experience lower levels of educational mismatch than individuals with non-vocational degrees (Levels et al. 2014; Wolbers 2003). In France, vocational degrees are often acquired through an apprenticeship, which increases the likelihood of a good match between one's qualifications and job (Rose 2005). Therefore, it is likely that the proportion of vocational graduates in a population group contributes to explaining its observed level of educational mismatch.

The third mechanism pertains to differential sorting into fields of study. Graduates from certain fields of study experience higher levels of educational mismatch than graduates from other fields. For example, arts and humanities graduates (Robst 2007; Wolbers 2003) and other programs with a general orientation (Verhaest et al. 2017) are more at risk of educational mismatch than health graduates (Somers et al. 2019). Evidence on the fields of study of the first and second generations in France is still scant. However, using Norwegian data, Borgen and Hermansen (2023) show that children of immigrants are over-represented in some fields, such as business administration and law, science and engineering, and health. If some of these fields of study are more (or, conversely, less) mismatch-prone, it could contribute to explaining a higher (or lower) level of mismatch in these groups.

Individual-level mechanisms, all relating to individuals' strategies and biographies, might also account for observed differences in the levels of educational mismatch between groups. We put forth three mechanisms, of which the first two concern the length of the job search. The first relates to recent unemployment spells, while the second refers to the school-to-work transition. We expect that individuals who experience long periods of unemployment, either recent or right after graduating, widen their job search and hence undergo higher levels of educational mismatch when they do find a job (Ordine and Rose 2015; Sam 2018), a pattern which is particularly present for early-career individuals in France (Nauze-Fichet and Tomasini 2002; Rose 2005).

Our third proposed individual-level mechanism relates to experiences of discrimination. We expect that past experiences of discrimination at work lead affected individuals to change employment sector, and in turn result in higher levels of educational mismatch. Ethnic, religious, and race-based discrimination in hiring and on the labor market is persistent from the first to the second generation among certain ethnic groups (Pager et al. 2009), and particularly widespread in France according to a recent meta-analysis of field experiments in Europe and

North America (Quillian et al. 2019). Immigrants and their descendants, who are perceived as Muslims, are commonly targeted in France (Adida et al. 2010, 2016). This mechanism may impact non-European immigrants' employment search but also that of their descendants.

## Hypotheses

Given the theoretical and empirical literature reviewed above, we hypothesize that vertical and horizontal mismatch levels differ across generations and origin groups. Following human capital theory, immigrants are expected to be over-educated due to imperfect international transferability of degrees and skills, while the second and third generation should have similar levels of educational mismatch as natives.

H1 - Transferability of degrees and skills hypothesis: We expect first-generation immigrants to exhibit significantly higher educational mismatch than natives, but no more difference by the second generation.

Alternatively, we may expect a more gradual process. According to the neo-classical assimilation framework, immigrants' integration is a slow intergenerational process of convergence with the native population. Higher educational mismatch may not have fully disappeared in the second, and even the third generation.

H2 - Gradual convergence hypothesis: We expect that the level of educational mismatch is highest in the first generation and then diminishes across generations, gradually converging towards the native population.

Segmented assimilation and related theories lead us to expect that patterns of convergence differ markedly across ethnic groups and that mismatch is more persistent among the descendants of racialized non-European immigrants.

H3 - Persistent segmentation hypothesis: We expect educational mismatch to decrease less, or perhaps not to decrease at all, between the first and subsequent generations among the descendants of non-European immigrants.

Gendered discrimination patterns on the labor market lead us to expect differences in the level of mismatch experienced by men and women. Male descendants of ethnic minority immigrants are expected to undergo higher education-occupation mismatch than women from the same ethnic group, as racialized men are more likely to experience discrimination on the labor market.

H4 - Gendered mismatch hypothesis: We expect that male descendants of immigrants experience more persistent differences in educational mismatch, relative to native men, than female descendants of immigrants, relative to native women.

Regarding the mechanisms, holding a "closed occupation", having vocational training, and graduating from a general or specific field of study lead to different levels of educational mismatch and can explain observed gaps in educational mismatch levels with natives.

H5 - Structural sorting hypothesis: We expect that group-specific sorting into "closed" occupations, vocational training, and fields of study contribute to explaining group differences in educational mismatch.

At the individual level, experiences of unemployment and discrimination are likely to affect individuals' job search strategies and lead them to accept jobs below their qualifications or outside of their field.

H6 - Individual job search hypothesis: We also expect that differences in experiences of unemployment and discrimination contribute to explaining group differences in educational mismatch.

## Data and Methods

## TeO2 Survey and Sample Restrictions

We use data from the new Trajectories and Origins 2 (TeO2) survey (Beauchemin et al. 2023). This large-scale ( $\mathrm{N}=27,500$ ), nationally representative, face-to-face survey oversamples immigrants and their descendants and thus provides a unique source of information to study these populations. In the French setting, an immigrant is an individual who was born abroad without the French nationality at birth. We distinguish between individuals who are themselves immigrants (henceforth called G1), those who are born in France to at least one immigrant parent (G2), and those who are born in France to parents born in France and have at least one immigrant grandparent (G3). We compare these generational status groups to natives (G4+) without immigrant ancestry (up to the grandparents' generation).

Among individuals with an immigrant background, persons come from a diverse set of geographic origins. The most common origins in the survey are North Africa, the Middle East (especially Turkey), Asia, and Southern Europe (especially Portugal and Italy). Based on prior
literature in France, we expect that the major line of distinction lies between European and nonEuropean origin groups (Beauchemin et al. 2018). Among non-European immigrants and their descendants, about $75 \%$ are from Africa (with Algeria, Morocco and Tunisia being frequent origin countries). The remaining $25 \%$ are largely from Southeast Asia and Turkey. Given that the distinction between European and non-European origins is salient in French society, as well as to garner enough statistical power, we distinguish between European and non-European origins in our analyses of whether patterns of assimilation are segmented.

We restrict our analytical sample to individuals for whom we have information on educational attainment (excluding 560 observations), field of study (excluding 3,963 observations), and who have an occupation at the time of the survey (excluding 2,163 observations who are studying and 3,699 observations who are not employed). We further exclude respondents born in France's overseas territories and their descendants (1,270 observations), as well as French foreign-born individuals and their descendants (2,796 individuals). Being neither immigrants nor natives, the excluded groups are quite specific to the French context and are beyond the scope of this paper. Our final analytical sample comprises 12,971 individuals, among whom 6,563 are men, and 6,408 are women.

## Measures of Educational Mismatch

The literature commonly uses three types of measures to capture mismatch: expert assessments of job requirements, subjective measures based on workers' perceptions of mismatch, and empirical measures based on the observed distribution of educational degrees in each occupation. Even though these indicators operationalize the same concept (Chiswick and Miller 2010), they can provide different results (Flisi et al. 2017; Groot and Maasen van den Brink 2000). Expert assessments of the degree required for an occupation are based on detailed job analysis. This measurement strategy implies exhaustive lists of standardized occupations, such as $\mathrm{O}^{*}$ Net codes in the US. Due to the costliness of the exercise, these measures are infrequently updated and often refer to broad occupational categories (Addison et al. 2020; Banerjee et al. 2019). This approach also adopts an employer's perspective and is only "objective" to the extent that it is not assessed by employees themselves. Subjective measures of employees' self-assessed mismatch provide more up-to-date information and may be more accurate in referring to the actual work individuals do. However, workers tend to overstate their job requirements and their level of over-education (Hartog 2000).

The present study uses empirical measures and follows an inductive approach of "realized matches" (Clogg and Shockey 1984), which is widely used (Li and Lu 2023). This
measure is based on the empirical distribution of educational attainment and fields of study within each occupation. The empirical approach constructs mismatch measures relative to the general population and has a number of strengths: it relies on up-to-date information, uses detailed occupation categories, and neutralizes any bias related to individual interpretations of the educational requirements for different occupations. However, we recognize that it also has some disadvantages compared to other measurement strategies. In particular, as an inductive approach relying on observed distributions, the empirical measure identifies deviations from the general population. If over-education-as measured by expert analysis or workers' subjective perceptions-is common in an occupation, then it becomes the statistical standard and will not be considered mismatch by the empirical measurement approach. Our measure can therefore be considered downwardly biased and provides conservative estimates of the prevalence of mismatch (Groot and Maasen van den Brink 2000; Johansson and Katz 2006).

To measure vertical mismatch, we rely on a distribution of educational attainment in 11 levels: Primary school; Middle school; Short vocational; Vocational baccalauréat; Technological and academic baccalauréat; Bac+2 years; $\mathrm{Bac}+3$ years; $\mathrm{Bac}+4$ years; $\mathrm{Bac}+5$ years; Elite schools (Grandes écoles); and PhD. Using the pooled French Labor Force surveys between 2013 and 2020, we compute the distributions of educational attainment in each occupation by gender at the most disaggregated occupational level (4-digit level of the French PCS nomenclature amounting to almost 500 occupations). We then locate the educational attainment of each TeO 2 respondent within the educational distribution of individuals of the same gender and detailed occupation. We calculate the "ridit" of this relative position (Bross 1958). This is a scaled percentile, which indicates for each respondent the proportion of the population within the same occupation holding a degree below or equal to that of the respondent. We z-standardize this variable so that a value above zero indicates over-education while a value below zero indicates under-education.

To measure horizontal mismatch, we rely on the distribution of fields of study using the International Standard Classification of Education (ISCED) field of study classification, in line with prior research (DiPrete et al. 2017). This provides us with 11 fields of study: Generic programs and qualifications; Education; Arts and humanities; Social sciences, journalism, and information; Business, administration, and law; Natural sciences, mathematics, and statistics; Information and communication technologies; Engineering, manufacturing, and construction; Agriculture, fishery, forestry, and veterinary; Health and welfare; and Services.

Similar to vertical mismatch, our measure of horizontal mismatch relies on reference distributions from the 2013-2020 French Labor Force surveys. For each of the 500 detailed
occupations, we compute the distribution of fields of study. For each TeO 2 respondent, we assess the proportion of individuals of the same gender in the same occupation who completed a different field of study. The variable is z-standardized. A lower value indicates that the individual's field of study is common among people with the same occupation (low horizontal mismatch), while a higher value indicates that their field of study is rare (high horizontal mismatch).

## Multivariate Analyses

We estimate linear regressions to assess differences in the level of vertical and horizontal mismatch experienced by immigrants (G1), children of immigrants (G2), grandchildren of immigrants (G3), and natives (G4+). Our two dependent variables of educational mismatch are continuous, enabling us to assess under- and over-education with regards to vertical mismatch, and how (un)common the field of study is in the occupation for horizontal mismatch. We run all analyses separately for men and women, as we expect educational mismatch patterns to be gendered.

We include a number of control variables to account for sociodemographic differences between the groups that likely contribute to differences in educational mismatch. We control for age and age squared because the age distribution of the groups differs and age (or birth cohort) can impact mismatch levels (Addison et al. 2020). Given that parts of the TeO 2 survey were conducted during the covid pandemic, we also include a dummy variable indicating whether the interview was conducted before or after March 2020 (first lockdown in France). The models further control for income terciles so as to compare individuals who hold broadly similar positions in the labor market. We control for income rather than occupation or educational attainment as these are used to construct the dependent variables. We provide the coefficients and standard errors of the control variables in Tables A1-A4 in the Appendix. The tables additionally include a second model that controls for years of education to compare individuals with similar amounts of education. Controlling for this variable does not change the general patterns observed.

## Main Findings

## Descriptive Results

Table 1 presents descriptive results across generations and origin groups. The most common education levels are short vocational training (26\%) and Bac+2 (18\%). Non-European immigrants and their descendants are somewhat less likely to have a short vocational training than the other groups ( $18 \%$ ) and non-European and European G1 are less likely to have a Bac+2 (13 and $12 \%$, respectively). The most common fields of study are business, administration and law, and engineering, manufacturing and construction (with about $25 \%$ completing either). Business, administration, and law is particularly common among non-European G2 and G3, while engineering, manufacturing, and construction is more prevalent among European G1, G2, G3, and natives.
[Table 1 about here]
Regarding occupations, we find that non-European and European G1 are more often manual workers than the other groups ( 23 and $20 \%$ versus the average of $18 \%$ ). However, these two groups are also somewhat more likely to be executives and higher professionals ( $23 \%$ versus the average of $20 \%$ ). In comparison, non-European and European G2 and G3 are more often intermediate professionals and non-manual workers than G1.

We find that vertical mismatch is highest in the first generation, especially among nonEuropean G1 (0.30). Mean values of vertical mismatch are also high among European G1 ( 0.20 ) when compared to those observed among natives ( -0.04 ). We observe a decrease in the level of vertical mismatch between G1 and G2 among both non-Europeans and Europeans. By contrast, mean levels of vertical mismatch increase again somewhat in the third generation. We will explore the extent to which this increase is due to differences in the demographic characteristics of G3 in the multivariate analyses below, e.g., that they are younger. This pattern of decline in mismatch between the first and second generation, and a re-increase in the third is also observed for horizontal mismatch. The remaining panels in Table 1 show mean values for the other independent variables.

## Vertical Mismatch

We begin by assessing whether the relative level of vertical mismatch experienced by immigrants, when compared to natives, diminishes across generations. Figure 1 shows results from linear regressions on vertical mismatch, with negative values indicating under-education
and positive ones over-education. Throughout the analysis we compare immigrants and their descendants to natives, represented by the vertical reference line. We find that G1 tend to be over-educated when compared to natives. However, this difference disappears by G2. In other words, we observe no evidence of over-education among G2 and G3 when compared to natives. We observe similar patterns for women and men, though vertical mismatch is slightly higher among G1 women than among G1 men. In short, G1 experience more over-education when compared to natives, while we find no evidence of persistent differences among G2 and G3.
[Figure 1 about here]
Given that average results by generation might conceal a great deal of heterogeneity between origin groups, Figure 2 presents results from similar models on vertical mismatch disaggregating generations between non-European and European origins. We find that both non-European and European G1 experience higher levels of vertical mismatch than natives. Among non-European G1, we observe similar relative levels of over-education among men and women. By contrast, European G1 women tend to have somewhat higher relative levels of over-education than European G1 men. Among G2 and G3, we observe no evidence of overeducation when compared to natives. These findings indicate that immigrants are overeducated when compared to natives, but that this difference is no longer perceptible by the second generation, regardless of geographic origin.
[Figure 2 about here]
In additional analyses, we investigate the connection between higher levels of vertical mismatch among G1 and the limited international transferability of foreign degrees. Specifically, we focus on G1 and differentiate between those who obtained their highest degree in France or abroad (see Figure A1). These analyses reveal that gaps with natives are smaller among G1 who obtained their degree in France than among those who have a foreign degree. This indicates that higher relative levels of vertical mismatch among G1 are mainly the result of over-education experienced among those with a foreign degree. We observe this pattern among European immigrants of both sexes, and non-European women. However, nonEuropean immigrant men who obtained their degree in France experience only slightly lower levels of vertical mismatch than those with a foreign degree. This suggests that this group faces additional barriers beyond difficulties in getting a foreign degree recognized.

## Horizontal Mismatch

We now assess horizontal mismatch across generations. Figure 3 shows that G1 experience higher levels of horizontal mismatch than natives, but by G2 and G3 the level of horizontal
mismatch is similar to that of natives. Patterns are similar for men and women, though G1 men experience somewhat higher relative levels of horizontal mismatch than G1 women.
[Figure 3 about here]
In Figure 4, we distinguish between non-European and European immigrants and their descendants, and note striking differences between origin groups. Among men, non-Europeans experience higher levels of horizontal mismatch when compared to natives across the three generations analyzed. In this group, the level of horizontal mismatch remains remarkably stable between G1 and G2, but is even somewhat higher among G3. Still, large confidence intervals indicate that the estimate for non-European G3 is relatively imprecise. Among European men, we observe higher relative levels of horizontal mismatch among G1 but no evidence of higher horizontal mismatch in subsequent generations. Among women, we similarly observe higher relative levels of horizontal mismatch among non-European and European G1 when compared to natives, but no significant difference among G2 or G3. In sum, our findings highlight an exception to the overall pattern of intergenerational convergence: sons and especially grandsons of non-European immigrants tend to experience significantly higher levels of horizontal mismatch than natives.
[Figure 4 about here]
Horizontal mismatch can be linked to negative or positive outcomes as, on the one hand, individuals with few opportunities expand their job search beyond their field of study, and, on the other hand, professionally successful individuals may also work outside of their initial field. We therefore present the occupations with the highest and lowest levels of horizontal mismatch and their average wages (see Table A5). These analyses show that occupations with the highest average horizontal mismatch tend to have a lower skill level and pay less than occupations with the lowest horizontal mismatch, indicating that higher levels of horizontal mismatch are generally linked to a penalty in the French context.

## Mechanisms

In order to gain an understanding of the potential processes underlying persistently higher levels of horizontal mismatch experienced by non-European men, we incorporate two sets of theoretically-motivated mechanisms discussed earlier. The first set of mechanisms refers to structural mechanisms and includes occupational closure, vocational training, and fields of study. The second set refers to individual-level mechanisms and includes recent unemployment spells, difficulties experienced in the school-to-work transition, and belonging to a discriminated group. We focus on men and horizontal mismatch in this analysis, as it is the
only case in which we observed persistent differences across generations. We estimate linear regressions and include indicators operationalizing each mechanism in separate models, and then altogether in a final model.

In Table 2, we express the coefficients estimating differences with natives as a percentage of the difference in the baseline model. In other words, we set the differences observed in the baseline model to 100 and reweight the coefficients observed in models $2-8$ to assess the extent to which differences between groups decline when we control for potential mechanisms. A percentage close to 100 indicates that differences do not decline substantially when we control for the mechanism. A percentage close to zero indicates that differences essentially disappear when we take the mechanism into account. Percentages can also take on negative values, indicating that the initial difference changes sign when we control for the mechanism, i.e., immigrants experience less horizontal mismatch than natives. Differences that remain significant are indicated in bold. Differences that are not significantly different from zero in the baseline model (prior to incorporating mechanisms) are shaded in gray. We provide the full set of coefficients and standard errors in Table A6 in the Appendix. This table also shows that the coefficients of all mechanisms are sizeable, significant, and in the expected directions.
[Table 2 about here]
We find that differences do not decline substantially when we control for occupational closure in model 2. For all groups, the numbers remain close to 100. By contrast, differences are halved for non-European and European G1 when we control for having completed vocational training in model 3. The difference between European G1 and natives becomes statistically non-significant, while the difference between non-European G1 and natives remains significant. For G2 or G3, controlling for vocational training does not lead to similar declines in horizontal mismatch. Importantly, when we control for sorting into fields of study in model 4 , differences decline for all groups and are no longer statistically different from zero. Differences in fields of study between groups thus appear to be a major mechanism in explaining observed gaps in horizontal mismatch for men of non-European origins.

Models 5-7 control for individual-level mechanisms. We find that differences do not decline considerably when we incorporate recent unemployment spells, difficulties experienced in the school-to-work transition, or belonging to a discriminated group. The observed differences remain statistically significant and fluctuate around 90. Still, belonging to a discriminated group explains a non-trivial part of the differences observed among nonEuropean G1 and G2. Specifically, differences decline from 100 to 82 and 70, respectively.

The final model includes all mechanisms and shows that differences are close to zero or negative, and never statistically significant. However, results from this model need to be interpreted with care, as the different mechanisms are correlated. Table 2 shows that, taken altogether, the mechanisms explain away differences between generations and origin groups to varying extents; in particular, sorting into fields of study appears to be a decisive mechanism.

An assessment of the distribution of the origin groups across fields of study reveals that non-European men are particularly over-represented in generic programs and qualifications, which is the field with the highest average levels of horizontal mismatch (see Table A7). They are also more frequently in social sciences, and arts and humanities, which are likewise fields with high levels of horizontal mismatch. Conversely, they are underrepresented in engineering, which, along with health and welfare, has the lowest level of mismatch.

## Sensitivity Analysis

We have run sensitivity analyses excluding generic programs and qualifications. This field is concentrated in the lowest educational level and does not provide a specialization. For vertical mismatch, including individuals with generic programs and qualifications may lead to lower estimates, as this group cannot experience over-education. By contrast, for horizontal mismatch it may lead to higher estimates, as individuals with generic programs did not specialize in a particular field and may search for a job in different fields of study. In the main analysis, we include generic programs and qualifications with the aim of studying the full working population and to avoid issues resulting from sample selection. When we exclude individuals with generic programs and qualifications in Table A8, we find similar patterns to those presented in the main analysis. Still, as expected differences in vertical mismatch are somewhat larger, and differences in horizontal mismatch are somewhat smaller.

We have also run the main analyses excluding small occupations to assess whether our results are driven by outliers. Small occupations refer to occupations with fewer than 5,000 individuals in the French Labor Force survey. Results reveal similar patterns for vertical and horizontal mismatch as in the main analysis (see Table A9).

## Discussion

In this study, we analyze the extent to which individuals' educational attainment and field of study match that of others in the same occupation. We assess whether the levels of vertical and horizontal mismatch experienced by immigrants, children of immigrants, and grandchildren of
immigrants differ from those of natives in France. Linear regression models estimated on data from the recent TeO 2 survey reveal high levels of vertical mismatch in the first generation, which converge towards those of natives by the second generation. By contrast, horizontal mismatch proves more durable, as higher levels persist across three generations among nonEuropean men.

These findings indicate distinct patterns for vertical and horizontal mismatch. Our results on vertical mismatch are in line with our first hypothesis (H1), according to which educational mismatch is the result of imperfect international transferability of degrees and skills. The human capital theory highlights obstacles in getting training accredited in the destination country, language difficulties, and incomplete institutional knowledge as the main factors underlying higher levels of educational mismatch among immigrants (Aleksynska and Tritah 2013; Chiswick and Miller 2010; Li and Lu 2023). Since these mechanisms are specific to the first generation, mismatch is expected to disappear in the second and third generations who were born and educated in France. Our findings corroborate this expectation and indicate that higher relative levels of vertical mismatch in the first generation are mainly the result of over-education experienced among immigrants with a foreign degree. This evidence is in line with recent empirical studies in the US ( Li and Lu 2023; Lu and Li 2021 ). Overall, these results underline that the descendants of immigrants, who are on the labor market, tend to have jobs that are consistent with their educational attainment-at least as much as natives. Still, it is important to keep in mind that immigrants' descendants who are employed constitute a selected group, as they face specific obstacles to enter paid employment (Meurs 2018), including racial discrimination (Quillian et al. 2019).

Our finding of convergence with natives in the level of vertical mismatch by the second generation paints a slightly more optimistic picture than previous studies. Prior work has noted higher levels of vertical mismatch among non-European G2 in Sweden (Dahlstedt 2015) and the Netherlands (Belfi et al. 2021). Beyond context-specific factors, these differences may be, in part, due to different measures of mismatch used (Groot and Maasen van den Brink 2000). We use an empirical measure, while the cited studies rely on subjective measures and expert assessments. Empirical measures are known to provide more conservative estimates of mismatch than the two other measures.

For horizontal mismatch, we instead observe persistent differences among nonEuropean men giving credence to our third hypothesis (H3), which posited the existence of enduring disadvantages among the descendants of non-European immigrants. This result qualifies the gradual convergence scenario (H2) following the neo-classical assimilation
framework (Alba and Nee 2003) and suggests lasting penalties for racialized men. This may be the result of discrimination experienced in the educational system and/or the labor market, as put forward by segmented assimilation theory (Portes and Zhou 1993; Zhou and Gonzales 2019) and theories of exclusion (Telles and Ortiz 2008). Indeed, occupations with the highest average horizontal mismatch tend to have lower skill levels and pay less than occupations with the lowest horizontal mismatch. This is in line with a review of research on this topic, showing that "horizontally mismatched workers generally incur a wage penalty, are less satisfied with their jobs, and are more likely to regret their study programme" (Somers et al. 2019:567). The persisting horizontal mismatch among non-European third generation men can therefore be considered a sign a durable disadvantage faced by this group.

For horizontal mismatch, we also find evidence in line with our fourth hypothesis (H4), which posited that men of immigrant descent would undergo more persistent educational mismatch than women as ethnic minority men are more often stereotyped as threatening than ethnic minority women (Sidanius and Pratto 2001). By contrast, for vertical mismatch we do not observe substantial gender differences. Hence, while both male and female immigrants experience imperfect international transferability of degrees, having a job outside of one's field of expertise is more common among men than women.

Our analysis of the potential mechanisms underlying different levels of horizontal mismatch across generations and origin groups indicates that structural sorting in the educational system plays the most important role (H5), significantly more important than individual-level experiences related to job search. The field of study explains the persistent horizontal mismatch among non-European men, while having a vocational training and belonging to a discriminated group also play a role. These mechanisms have also been highlighted as potentially powerful determinants of horizontal mismatch in previous work (Somers et al. 2019:583). We further find that the descendants of immigrants are overrepresented in fields of study that are loosely linked to occupations, which can explain persistently higher levels of horizontal mismatch (Rose 2005). These differences may result from differences in school tracking at earlier ages (Primon et al. 2018). In addition, the descendants of immigrants and natives appear to choose their field of study differently. The descendants of immigrants are more prone to pursue fields because they lacked information on alternative fields or because they did not get accepted into their first choice (Belghith et al. 2020; Palheta 2015) (Belghith et al. 2020; Palheta 2015). A recent discrimination test accordingly suggests that students with North African-sounding names are more likely to be penalized in their choice of graduate studies (Chareyron et al. 2022). This points to the fact that
non-European men face discrimination in the educational system and are possibly relegated to economically unviable fields of study, ultimately increasing the likelihood of experiencing horizontal mismatch.

Our study has a few limitations. First, we compare generations whose parents (for G2) and grandparents (for G3) migrated to France at different periods, which may affect mismatch patterns across the groups. Our approach in addressing this concern is to control for observable differences in sociodemographic characteristics across the groups. Second, we provide suggestive evidence that higher levels of horizontal mismatch are negatively related to achievement in the labor market, leading to likely disadvantages among non-European men, but do not fully investigate this aspect. Further analysis will be needed to address the potential negative labor market consequences of horizontal mismatch in the second and third generations.

## Conclusion

We find that over-education is primarily experienced by first-generation immigrants, whereas the descendants of immigrants have similar levels of vertical mismatch as natives. However, men from non-European descent experience persistently higher levels of horizontal mismatch, even in the third generation.

This study contributes to the literature, first, by extending educational mismatch research to the third generation. Another contribution lies in our joint analysis of vertical and horizontal mismatch which revealed a specific persistence in horizontal mismatch among grandsons of non-European immigrants. Finally, in addition to uncovering descriptive patterns of educational mismatch, we have shown that a major mechanism explaining persistently high horizontal mismatch among immigrants' descendants is their overrepresentation in specific fields of study in the French educational system.

Acknowledgements: We are grateful to Xavier St-Denis, Lucas Drouhot, and Ugo Palheta for their comments on earlier versions of this draft. We would also like to thank participants at the 2023 Population Association of America conference in New Orleans, the 2022 RC28 Spring meeting at the London School of Economics, and 3GEN-project team members for their helpful input. This work was supported by the Agence Nationale de la Recherche (Grant number ANR-20-CE41-0001) and Swedish Research Council for Health, Working life and Welfare (Förskiningsrådet för Hälsa, Arbetsliv och Välfärd, Grant number 2021-00026).

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## Tables

Table 1 Weighted distributions of educational attainment, the field of study, occupations, and demographic characteristics across generations and origin groups

|  | non-European |  |  |  | European |  | Natives |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | G1 | G2 | G3 | G1 | G2 | G3 | G4+ | Total |
| Educational attainment |  |  |  |  |  |  |  |  |
| Primary school | 2 | 0 | 2 | 1 | 0 | 0 | 1 | 1 |
| Middle school | 8 | 5 | 4 | 7 | 4 | 6 | 5 | 5 |
| Short vocational | 17 | 19 | 18 | 20 | 30 | 26 | 27 | 26 |
| Vocational bac | 7 | 14 | 13 | 7 | 11 | 10 | 10 | 10 |
| Academic bac | 13 | 11 | 21 | 13 | 10 | 11 | 11 | 11 |
| Bac+2 | 13 | 18 | 15 | 12 | 18 | 18 | 19 | 18 |
| Bac+3 | 11 | 12 | 7 | 12 | 10 | 9 | 12 | 11 |
| Bac+4 | 4 | 4 | 4 | 5 | 5 | 3 | 3 | 4 |
| Bac+5 | 16 | 12 | 12 | 13 | 7 | 11 | 7 | 9 |
| Grandes écoles | 6 | 3 | 4 | 4 | 3 | 3 | 3 | 3 |
| PhD | 5 | 2 | 1 | 7 | 2 | 2 | 2 | 2 |
| Field of study |  |  |  |  |  |  |  |  |
| Generic program and qualifications | 11 | 6 | 9 | 10 | 4 | 7 | 5 | 6 |
| Teaching | 1 | 1 | 2 | 2 | 1 | 2 | 2 | 2 |
| Arts and humanities | 10 | 5 | 7 | 14 | 8 | 4 | 6 | 7 |
| Social sciences, journalism, and information | 6 | 7 | 10 | 6 | 5 | 6 | 5 | 5 |
| Business, administration, and law | 23 | 36 | 29 | 20 | 29 | 23 | 24 | 25 |
| Natural sciences, mathematics, and statistics | 7 | 4 | 3 | 7 | 4 | 5 | 4 | 4 |
| Information and communication technologies | 7 | 3 | 1 | 2 | 2 | 2 | 2 | 2 |
| Engineering, manufacturing, and construction | 23 | 20 | 20 | 26 | 29 | 28 | 28 | 27 |
| Agriculture | 1 | 1 | 0 | 1 | 2 | 4 | 4 | 3 |
| Health and welfare | 7 | 11 | 10 | 8 | 9 | 12 | 12 | 11 |
| Services | 4 | 5 | 9 | 4 | 7 | 9 | 7 | 7 |

[^1]Table 1 Continued

|  | non-European |  |  | European |  |  | Natives | Total |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | G1 | G2 | G3 | G1 | G2 | G3 | G4+ |  |
| Occupation (PCS) |  |  |  |  |  |  |  |  |
| Farmers | 0 | 0 | 0 | 1 | 1 | 0 | 2 | 1 |
| Craftsmen, merchants, and company managers | 6 | 6 | 9 | 8 | 7 | 6 | 6 | 6 |
| Executives and higher professionals | 23 | 20 | 16 | 23 | 22 | 22 | 20 | 20 |
| Intermediate occupations | 22 | 32 | 24 | 27 | 30 | 27 | 31 | 30 |
| Non-manual workers | 26 | 29 | 34 | 21 | 25 | 28 | 24 | 25 |
| Manual workers | 23 | 13 | 16 | 20 | 16 | 17 | 18 | 18 |
| Mismatch |  |  |  |  |  |  |  |  |
| Mean vertical mismatch | 0.30 | 0.04 | 0.08 | 0.20 | -0.10 | 0.01 | -0.04 | 0.00 |
| Mean horizontal mismatch | 0.20 | 0.03 | 0.25 | 0.11 | -0.08 | 0.07 | -0.04 | 0.00 |
| Demographic characteristics |  |  |  |  |  |  |  |  |
| Female | 44 | 49 | 46 | 52 | 46 | 50 | 49 | 49 |
| Mean age at interview | 41 | 36 | 33 | 42 | 43 | 41 | 41 | 41 |
| Interviewed during the covid pandemic (March 2020 and after) | 1 | 67 | 56 | 1 | 65 | 7 | 0 | 9 |
| Income terciles |  |  |  |  |  |  |  |  |
| Tercile 1 | 38 | 34 | 34 | 41 | 36 | 32 | 34 | 34 |
| Tercile 2 | 35 | 35 | 39 | 28 | 32 | 36 | 35 | 35 |
| Tercile 3 (top) | 26 | 31 | 27 | 31 | 32 | 32 | 31 | 31 |
| Mean years of education | 18 | 18 | 17 | 17 | 18 | 18 | 18 | 18 |
| N | 3,715 | 2,880 | 485 | 1,462 | 1,602 | 709 | 2,118 | 12,971 |

Notes: Percentage within each group reported. Bac refers to baccalauréat. Bac +2 refers to shorter vocational studies, i.e., having passed the academic baccalauréat and completed 2 years of university studies. Bac +3 is equivalent to having completed a Bachelor degree. Bac +4 and $\mathrm{Bac}+5$ distinguish between one- and two-year Master programs. Elite schools (Grandes écoles) refer to universities that are highly competitive, comparable to Ivy league institutions in the US. Data are from authors' calculations.

Table 2 Weighted results from OLS regressions estimating horizontal mismatch across generations and origin groups for men

|  | $(1)$ |  | $(2)$ | $(3)$ | $(4)$ | (5) | (6) | (7) | (8) |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Generations and origin groups |  |  |  |  |  |  |  |  |  |
| (ref. natives G4+) | $0.30^{* * *}$ | $\mathbf{1 0 0}$ | $\mathbf{9 8}$ | $\mathbf{5 9}$ | -13 | $\mathbf{9 7}$ | $\mathbf{9 7}$ | $\mathbf{8 2}$ | $\mathbf{- 3 2}$ |
| non-European G1 | $0.25^{* * *}$ | $\mathbf{1 0 0}$ | $\mathbf{9 8}$ | $\mathbf{9 6}$ | 21 | $\mathbf{9 4}$ | $\mathbf{9 7}$ | $\mathbf{7 0}$ | -12 |
| non-European G2 | $0.43^{* * *}$ | $\mathbf{1 0 0}$ | $\mathbf{9 9}$ | $\mathbf{9 7}$ | 30 | $\mathbf{1 0 3}$ | $\mathbf{1 0 1}$ | $\mathbf{9 2}$ | 26 |
| non-European G3 | $0.15^{*}$ | $\mathbf{1 0 0}$ | $\mathbf{9 9}$ | 66 | -28 | $\mathbf{9 4}$ | $\mathbf{1 0 2}$ | $\mathbf{9 3}$ | -35 |
| European G1 | 0.03 | 100 | 82 | 148 | -8 | 89 | 127 | 98 | -21 |
| European G2 | 0.08 | 100 | 95 | 90 | 85 | 92 | 110 | 95 | 78 |
| European G3 |  |  |  |  |  |  |  |  |  |
| Structural mechanisms |  |  | Yes |  |  |  |  |  | Yes |
| Occupational closure |  |  | Yes |  |  |  |  | Yes |  |
| Vocational training |  |  |  | Yes |  |  |  | Yes |  |
| Sorting into fields of study |  |  |  |  |  |  |  | Yes |  |
| Individual-level mechanisms |  |  |  |  | Yes |  |  | Yes |  |
| Recent unemployment spells |  |  |  |  |  | Yes |  | Yes |  |
| School-to-work transition |  |  |  |  |  |  |  |  | Yes |
| Belonging to a discriminated group |  |  |  |  |  |  |  |  |  |

Notes: The regressions include controls for age at interview, age at interview squared, an indicator variable of whether the individual was interviewed during the covid pandemic (March 2020 and after), and income terciles. Significant differences from zero are indicated in bold. The full set of estimates and standard errors are provided in Table A6 in the Appendix.

* $\mathrm{p}<.05 ; * * * \mathrm{p}<.001$


## Figures and Figure Titles



Figure 1 Weighted coefficients from OLS regressions estimating vertical mismatch across generations. Natives are the reference group (indicated by the vertical line). Vertical mismatch is operationalized using information on the standardized ridit. Values above zero for standardized ridits indicate over-education, while values below zero indicate undereducation. Model 1 controls for age at interview, age at interview squared, an indicator variable of whether the individual was interviewed during the covid pandemic (March 2020 and after), and income terciles. Coefficients and standard errors are provided in Table A1 in the Appendix.


Figure 2 Weighted coefficients from OLS regressions estimating vertical mismatch across generations and origin groups. Natives are the reference group (indicated by the vertical line). Vertical mismatch is operationalized using information on the standardized ridit. Values above zero for standardized ridits indicate over-education, while values below zero indicate under-education. The model controls for age at interview, age at interview squared, an indicator variable of whether the individual was interviewed during the covid pandemic (March 2020 and after), and income terciles. Coefficients and standard errors are provided in Table A2 in the Appendix.


Figure 3 Weighted coefficients from OLS regressions estimating horizontal mismatch across generations. Natives are the reference group (indicated by the vertical line). Horizontal mismatch is operationalized using a standardized measure. Higher values indicate higher levels of horizontal mismatch, i.e., a small proportion of individuals in the occupation with the same field of study relatively speaking. The model controls for age at interview, age at interview squared, an indicator variable of whether the individual was interviewed during the covid pandemic (March 2020 and after), and income terciles. Coefficients and standard errors are provided in Table A3 in the Appendix.


Figure 4 Weighted coefficients from OLS regressions estimating horizontal mismatch across generations and origin groups. Natives are the reference group (indicated by the vertical line). Horizontal mismatch is operationalized using a standardized measure. Higher values indicate higher levels of horizontal mismatch, i.e., a small proportion of individuals in the occupation with the same field of study relatively speaking. The model controls for age at interview, age at interview squared, an indicator variable of whether the individual was interviewed during the covid pandemic (March 2020 and after), and income terciles. Coefficients and standard errors are provided in Table A4 in the Appendix.

## Appendix

Table A1 Weighted coefficients from OLS regressions estimating vertical mismatch across generations

|  | Male |  | Female |  |
| :---: | :---: | :---: | :---: | :---: |
|  | (1) | (2) | (1) | (2) |
| Generations (ref. natives G4+) |  |  |  |  |
| G1 | $\begin{gathered} 0.26^{* * *} \\ (0.05) \end{gathered}$ | $\begin{gathered} 0.26 * * * \\ (0.04) \end{gathered}$ | $\begin{gathered} 0.35 * * * \\ (0.05) \end{gathered}$ | $\begin{gathered} 0.35 * * * \\ (0.05) \end{gathered}$ |
| G2 | $\begin{gathered} -0.05 \\ (0.06) \end{gathered}$ | $\begin{gathered} -0.07 \\ (0.06) \end{gathered}$ | $\begin{gathered} -0.01 \\ (0.06) \end{gathered}$ | $\begin{gathered} -0.03 \\ (0.05) \end{gathered}$ |
| G3 | $\begin{gathered} -0.08 \\ (0.10) \end{gathered}$ | $\begin{gathered} -0.06 \\ (0.09) \end{gathered}$ | $\begin{aligned} & 0.16^{*} \\ & (0.08) \end{aligned}$ | $\begin{gathered} 0.13 \\ (0.08) \end{gathered}$ |
| Demographic characteristics |  |  |  |  |
| Age at interview | $\begin{gathered} 0.03 \\ (0.02) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.02) \end{gathered}$ | $\begin{gathered} 0.06 * * \\ (0.02) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.02) \end{gathered}$ |
| Age at interview squared | $\begin{gathered} -0.01 * * \\ (0.01) \end{gathered}$ | $\begin{gathered} -0.01 \\ (0.01) \end{gathered}$ | $\begin{gathered} -0.01 * * * \\ (0.01) \end{gathered}$ | $\begin{gathered} -0.01 \\ (0.01) \end{gathered}$ |
| Interviewed during the covid pandemic (March 2020 and after) | $\begin{gathered} -0.01 \\ (0.06) \end{gathered}$ | $\begin{gathered} -0.01 \\ (0.05) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.05) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.05) \end{gathered}$ |
| Income terciles (ref. tercile 1) |  |  |  |  |
| Tercile 2 | $\begin{gathered} -0.04 \\ (0.06) \end{gathered}$ | $\begin{gathered} 0.08 \\ (0.06) \end{gathered}$ | $\begin{gathered} -0.03 \\ (0.06) \end{gathered}$ | $\begin{gathered} 0.03 \\ (0.06) \end{gathered}$ |
| Tercile 3 (top) | $\begin{gathered} -0.08 \\ (0.06) \end{gathered}$ | $\begin{gathered} -0.11 \\ (0.06) \end{gathered}$ | $\begin{gathered} -0.11 \\ (0.07) \end{gathered}$ | $\begin{gathered} -0.21^{* *} \\ (0.07) \end{gathered}$ |
| Years of education |  | $\begin{gathered} 0.08 * * * \\ (0.01) \end{gathered}$ |  | $\begin{gathered} 0.07 * * * \\ (0.01) \end{gathered}$ |
| Constant | $\begin{gathered} 0.11 \\ (0.38) \end{gathered}$ | $\begin{gathered} -0.90^{*} \\ (0.01) \end{gathered}$ | $\begin{gathered} -0.61 \\ (0.42) \end{gathered}$ | $\begin{gathered} -1.29^{* * *} \\ (0.37) \end{gathered}$ |
| $\mathrm{R}^{2}$ | 0.09 | 0.20 | 0.08 | 0.18 |
| N | 6,563 | 6,563 | 6,408 | 6,408 |

Notes: Robust standard errors at the individual level in parentheses. Data are from authors' calculations.

* p < . 05 ; ** p < . $01 ;$ *** p < . 001

Table A2 Weighted coefficients from OLS regressions estimating vertical mismatch across generations and origin groups

|  | Male |  | Female |  |
| :---: | :---: | :---: | :---: | :---: |
|  | (1) | (2) | (1) | (2) |
| Generations and origin groups (ref. natives G4+) |  |  |  |  |
| non-European G1 | $\begin{gathered} 0.30^{* * *} \\ (0.05) \end{gathered}$ | $\begin{gathered} 0.27 * * * \\ (0.05) \end{gathered}$ | $\begin{gathered} 0.35 * * * \\ (0.06) \end{gathered}$ | $\begin{gathered} 0.34^{* * *} \\ (0.05) \end{gathered}$ |
| non-European G2 | $\begin{gathered} -0.11 \\ (0.07) \end{gathered}$ | $\begin{aligned} & -0.14^{*} \\ & (0.06) \end{aligned}$ | $\begin{gathered} 0.01 \\ (0.06) \end{gathered}$ | $\begin{gathered} -0.02 \\ (0.06) \end{gathered}$ |
| non-European G3 | $\begin{gathered} -0.25 \\ (0.16) \end{gathered}$ | $\begin{gathered} -0.16 \\ (0.15) \end{gathered}$ | $\begin{gathered} 0.14 \\ (0.14) \end{gathered}$ | $\begin{gathered} 0.15 \\ (0.14) \end{gathered}$ |
| European G1 | $\begin{aligned} & 0.17^{*} \\ & (0.07) \end{aligned}$ | $\begin{gathered} 0.23 * * * \\ (0.06) \end{gathered}$ | $\begin{gathered} 0.36 * * * \\ (0.06) \end{gathered}$ | $\begin{gathered} 0.36^{* * *} \\ (0.06) \end{gathered}$ |
| European G2 | $\begin{gathered} -0.04 \\ (0.07) \end{gathered}$ | $\begin{gathered} -0.03 \\ (0.06) \end{gathered}$ | $\begin{gathered} -0.03 \\ (0.06) \end{gathered}$ | $\begin{gathered} -0.04 \\ (0.06) \end{gathered}$ |
| European G3 | $\begin{aligned} & -0.06 \\ & (0.11) \end{aligned}$ | $\begin{aligned} & -0.05 \\ & (0.10) \end{aligned}$ | $\begin{gathered} 0.16 \\ (0.09) \end{gathered}$ | $\begin{gathered} 0.13 \\ (0.08) \end{gathered}$ |
| Demographic characteristics |  |  |  |  |
| Age at interview | $\begin{gathered} 0.03 \\ (0.02) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.02) \end{gathered}$ | $\begin{gathered} 0.06 * * \\ (0.02) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.02) \end{gathered}$ |
| Age at interview squared | $\begin{gathered} -0.01 * * \\ (0.01) \end{gathered}$ | $\begin{gathered} -0.01 \\ (0.01) \end{gathered}$ | $\begin{gathered} -0.01 * * * \\ (0.01) \end{gathered}$ | $\begin{gathered} -0.01 \\ (0.01) \end{gathered}$ |
| Interviewed during the covid pandemic (March 2020 and after) | $\begin{gathered} 0.02 \\ (0.06) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.06) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.05) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.05) \end{gathered}$ |
| Income terciles (ref. tercile 1) |  |  |  |  |
| Tercile 2 | $\begin{gathered} -0.04 \\ (0.06) \end{gathered}$ | $\begin{gathered} 0.08 \\ (0.06) \end{gathered}$ | $\begin{gathered} -0.03 \\ (0.06) \end{gathered}$ | $\begin{gathered} 0.03 \\ (0.06) \end{gathered}$ |
| Tercile 3 (top) | $\begin{gathered} -0.08 \\ (0.06) \end{gathered}$ | $\begin{aligned} & -0.11 \\ & (0.06) \end{aligned}$ | $\begin{gathered} -0.11 \\ (0.07) \end{gathered}$ | $\begin{gathered} -0.21^{* *} \\ (0.07) \end{gathered}$ |
| Years of education |  | $\begin{gathered} 0.08^{* * *} \\ (0.01) \end{gathered}$ |  | $\begin{gathered} 0.08 * * * \\ (0.01) \end{gathered}$ |
| Constant | $\begin{gathered} 0.13 \\ (0.38) \end{gathered}$ | $\begin{aligned} & -0.88^{*} \\ & (0.36) \end{aligned}$ | $\begin{gathered} -0.61 \\ (0.42) \end{gathered}$ | $\begin{gathered} -1.29 * * * \\ (0.37) \end{gathered}$ |
| $\mathrm{R}^{2}$ | 0.10 | 0.20 | 0.08 | 0.18 |
| N | 6,563 | 6,563 | 6,408 | 6,408 |

Notes: Robust standard errors at the individual level in parentheses. Data are from authors' calculations.

$$
* \mathrm{p}<.05 ; * * \mathrm{p}<.01 ; * * * \mathrm{p}<.001
$$

Table A3 Weighted coefficients from OLS regressions estimating horizontal mismatch across generations

|  | Male |  | Female |  |
| :---: | :---: | :---: | :---: | :---: |
|  | (1) | (2) | (1) | (2) |
| Generations (ref. natives G4+) |  |  |  |  |
| G1 | $\begin{gathered} 0.25 * * * \\ (0.05) \end{gathered}$ | $\begin{gathered} 0.25 * * * \\ (0.05) \end{gathered}$ | $\begin{gathered} 0.19 * * * \\ (0.05) \end{gathered}$ | $\begin{gathered} 0.19^{* * *} \\ (0.05) \end{gathered}$ |
| G2 | $\begin{gathered} 0.11 \\ (0.06) \end{gathered}$ | $\begin{gathered} 0.10 \\ (0.06) \end{gathered}$ | $\begin{aligned} & -0.07 \\ & (0.06) \end{aligned}$ | $\begin{aligned} & -0.06 \\ & (0.06) \end{aligned}$ |
| G3 | $\begin{gathered} 0.12 \\ (0.10) \end{gathered}$ | $\begin{gathered} 0.13 \\ (0.10) \end{gathered}$ | $\begin{gathered} 0.15 \\ (0.09) \end{gathered}$ | $\begin{gathered} 0.17 \\ (0.09) \end{gathered}$ |
| Demographic characteristics |  |  |  |  |
| Age at interview | $\begin{gathered} 0.01 \\ (0.02) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.02) \end{gathered}$ | $\begin{aligned} & -0.01 \\ & (0.02) \end{aligned}$ | $\begin{gathered} 0.01 \\ (0.02) \end{gathered}$ |
| Age at interview squared | $\begin{aligned} & -0.01 \\ & (0.01) \end{aligned}$ | $\begin{aligned} & -0.01 \\ & (0.01) \end{aligned}$ | $\begin{gathered} 0.01 \\ (0.01) \end{gathered}$ | $\begin{aligned} & -0.01 \\ & (0.01) \end{aligned}$ |
| Interviewed during the covid pandemic (March 2020 and after) | $\begin{gathered} 0.05 \\ (0.06) \end{gathered}$ | $\begin{gathered} 0.05 \\ (0.06) \end{gathered}$ | $\begin{aligned} & -0.02 \\ & (0.06) \end{aligned}$ | $\begin{aligned} & -0.01 \\ & (0.06) \end{aligned}$ |
| Income terciles (ref. tercile 1) |  |  |  |  |
| Tercile 2 | $\begin{gathered} 0.06 \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.09 \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.06) \end{gathered}$ | $\begin{aligned} & -0.02 \\ & (0.06) \end{aligned}$ |
| Tercile 3 (top) | $\begin{gathered} 0.08 \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.07 \\ (0.07) \end{gathered}$ | $\begin{gathered} -0.27 * * * \\ (0.07) \end{gathered}$ | $\begin{gathered} -0.22 * * \\ (0.08) \end{gathered}$ |
| Years of education |  | $\begin{gathered} 0.02 * * * \\ (0.01) \end{gathered}$ |  | $\begin{gathered} -0.03 * * * \\ (0.01) \end{gathered}$ |
| Constant | $\begin{aligned} & -0.37 \\ & (0.39) \end{aligned}$ | $\begin{aligned} & -0.66 \\ & (0.40) \end{aligned}$ | $\begin{gathered} 0.16 \\ (0.37) \end{gathered}$ | $\begin{gathered} 0.44 \\ (0.39) \end{gathered}$ |
| $\mathrm{R}^{2}$ | 0.01 | 0.02 | 0.03 | 0.04 |
| N | 6,563 | 6,563 | 6,408 | 6,408 |

Notes: Robust standard errors at the individual level in parentheses. Data are from authors' calculations.

* p < . $05 ;$ ** $\mathrm{p}<.01 ;$ *** $\mathrm{p}<.001$

Table A4 Weighted coefficients from OLS regressions estimating horizontal mismatch across generations and origin groups

|  | Male |  | Female |  |
| :---: | :---: | :---: | :---: | :---: |
|  | (1) | (2) | (1) | (2) |
| Generations and origin groups (ref. natives G4+) |  |  |  |  |
| non-European G1 | $\begin{gathered} 0.30^{* * *} \\ (0.05) \end{gathered}$ | $\begin{gathered} 0.29 * * * \\ (0.05) \end{gathered}$ | $\begin{gathered} 0.20 * * * \\ (0.05) \end{gathered}$ | $\begin{gathered} 0.21^{* * *} \\ (0.05) \end{gathered}$ |
| non-European G2 | $\begin{gathered} 0.25 * * * \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.25 * * * \\ (0.07) \end{gathered}$ | $\begin{gathered} -0.05 \\ (0.06) \end{gathered}$ | $\begin{gathered} -0.04 \\ (0.06) \end{gathered}$ |
| non-European G3 | $\begin{gathered} 0.43 * * * \\ (0.13) \end{gathered}$ | $\begin{gathered} 0.46 * * * \\ (0.13) \end{gathered}$ | $\begin{gathered} 0.18 \\ (0.11) \end{gathered}$ | $\begin{gathered} 0.18 \\ (0.11) \end{gathered}$ |
| European G1 | $\begin{aligned} & 0.15^{*} \\ & (0.07) \end{aligned}$ | $\begin{aligned} & 0.17 * \\ & (0.07) \end{aligned}$ | $\begin{gathered} 0.16 * * \\ (0.06) \end{gathered}$ | $\begin{gathered} 0.16 * * \\ (0.06) \end{gathered}$ |
| European G2 | $\begin{gathered} 0.03 \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.04 \\ (0.07) \end{gathered}$ | $\begin{gathered} -0.08 \\ (0.06) \end{gathered}$ | $\begin{gathered} -0.08 \\ (0.06) \end{gathered}$ |
| European G3 | $\begin{gathered} 0.08 \\ (0.11) \end{gathered}$ | $\begin{gathered} 0.09 \\ (0.11) \end{gathered}$ | $\begin{gathered} 0.15 \\ (0.09) \end{gathered}$ | $\begin{gathered} 0.17 \\ (0.10) \end{gathered}$ |
| Demographic characteristics |  |  |  |  |
| Age at interview | $\begin{gathered} 0.01 \\ (0.02) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.02) \end{gathered}$ | $\begin{gathered} -0.01 \\ (0.02) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.02) \end{gathered}$ |
| Age at interview squared | $\begin{gathered} -0.01 \\ (0.01) \end{gathered}$ | $\begin{gathered} -0.01 \\ (0.01) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.01) \end{gathered}$ | $\begin{gathered} -0.01 \\ (0.01) \end{gathered}$ |
| Interviewed during the covid pandemic (March 2020 and after) | $\begin{gathered} -0.01 \\ (0.06) \end{gathered}$ | $\begin{gathered} -0.01 \\ (0.06) \end{gathered}$ | $\begin{gathered} -0.02 \\ (0.05) \end{gathered}$ | $\begin{gathered} -0.02 \\ (0.05) \end{gathered}$ |
| Income terciles (ref. tercile 1) |  |  |  |  |
| Tercile 2 | $\begin{gathered} 0.06 \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.10 \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.06) \end{gathered}$ | $\begin{gathered} -0.02 \\ (0.06) \end{gathered}$ |
| Tercile 3 (top) | $\begin{gathered} 0.08 \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.07 \\ (0.07) \end{gathered}$ | $\begin{gathered} -0.27 * * * \\ (0.07) \end{gathered}$ | $\begin{gathered} -0.23^{* *} \\ (0.08) \end{gathered}$ |
| Years of education |  | $\begin{gathered} 0.02 * * * \\ (0.01) \end{gathered}$ |  | $\begin{gathered} -0.03 * * * \\ (0.01) \end{gathered}$ |
| Constant | $\begin{gathered} -0.39 \\ (0.39) \end{gathered}$ | $\begin{aligned} & -0.68 \\ & (0.40) \end{aligned}$ | $\begin{gathered} -0.16 \\ (0.38) \end{gathered}$ | $\begin{gathered} 0.44 \\ (0.39) \end{gathered}$ |
| $\mathrm{R}^{2}$ | 0.01 | 0.02 | 0.03 | 0.04 |
| N | 6,563 | 6,563 | 6,408 | 6,408 |

Notes: Robust standard errors at the individual level in parentheses. Data are from authors' calculations.

* p < . 05 ; ** p < . $01 ;$ *** p < . 001

Table A5 Ten occupations with the (A) highest and (B) lowest horizontal mismatch and their mean income

| A. Highest horizontally mismatched occupations | Mean <br> income |
| :--- | :---: |
| 01_215c: Craft pork butchers | 1087.5 |
| 02_633c: Car electricians, electronics technicians | 1822.6 |
| 03_212a: Agricultural machinery mechanics | 1935.4 |
| 04_215d: Food craftspeople | 3009.6 |
| 05_214b: Mechanical woodworkers | 3198.5 |
| 06_214d: Building materials manufacturers | 3830.9 |
| 07_673a: Unskilled metal-cutting production workers | 1675.9 |
| 08_542b: Typists, word-processing operators | 1915.3 |
| 09_632h: Carpet floorers | 1986.1 |
| 10_651b: Heavy shunting machine operators | 2024.3 |
|  | Mean |
| B. Lowest horizontally mismatched occupations | income |
| 01_312b: Notaries | 2984.9 |
| 02_312a: Lawyers | 4817.7 |
| 03_431d: Specialist nurses | 2733.6 |
| 04_431e: Midwives | 2297.5 |
| 05_311b: General practitioners | 3901.6 |
| 06_344b: Non-hospital salaried doctors | 4701.0 |
| 07_311a: Private specialist doctors | 12083.6 |
| 08_634a: Skilled car body repairers | 1762.0 |
| 09_311f: Private pharmacists | 4352.1 |
| 10_312c: Chartered accountants | 4464.9 |

[^2]Table A6 Weighted coefficients from OLS regressions estimating horizontal mismatch across generations and origin groups, among men

|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Generations and origin groups (ref. natives G4+) non-European G1 | $\begin{gathered} 0.30^{* * *} \\ (0.05) \end{gathered}$ | $\begin{gathered} 0.29 * * * \\ (0.05) \end{gathered}$ | $\begin{gathered} 0.17 * * * \\ (0.05) \end{gathered}$ | $\begin{aligned} & -0.04 \\ & (0.04) \end{aligned}$ | $\begin{gathered} 0.29 * * * \\ (0.05) \end{gathered}$ | $\begin{gathered} 0.29 * * * \\ (0.06) \end{gathered}$ | $\begin{gathered} 0.24 * * * \\ (0.06) \end{gathered}$ | $\begin{gathered} -0.09 * \\ (0.04) \end{gathered}$ |
| non-European G2 | $\begin{gathered} 0.25 * * * \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.25 * * * \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.24 * * * \\ (0.06) \end{gathered}$ | $\begin{gathered} 0.05 \\ (0.05) \end{gathered}$ | $\begin{gathered} 0.24 * * * \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.25 * * * \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.18 * * \\ (0.07) \end{gathered}$ | $\begin{aligned} & -0.03 \\ & (0.06) \end{aligned}$ |
| non-European G3 | $\begin{gathered} 0.43 * * * \\ (0.13) \end{gathered}$ | $\begin{gathered} 0.43 * * * \\ (0.13) \end{gathered}$ | $\begin{gathered} 0.42 * * * \\ (0.12) \end{gathered}$ | $\begin{gathered} 0.13 \\ (0.11) \end{gathered}$ | $\begin{gathered} 0.44 * * * \\ (0.13) \end{gathered}$ | $\begin{gathered} 0.44 * * * \\ (0.13) \end{gathered}$ | $\begin{gathered} 0.40 * * \\ (0.13) \end{gathered}$ | $\begin{gathered} 0.11 \\ (0.10) \end{gathered}$ |
| European G1 | $\begin{aligned} & 0.15^{*} \\ & (0.07) \end{aligned}$ | $\begin{aligned} & 0.15^{*} \\ & (0.07) \end{aligned}$ | $\begin{gathered} 0.10 \\ (0.06) \end{gathered}$ | $\begin{aligned} & -0.04 \\ & (0.05) \end{aligned}$ | $\begin{aligned} & 0.14^{*} \\ & (0.07) \end{aligned}$ | $\begin{aligned} & 0.15^{*} \\ & (0.07) \end{aligned}$ | $\begin{aligned} & 0.14^{*} \\ & (0.07) \end{aligned}$ | $\begin{aligned} & -0.05 \\ & (0.05) \end{aligned}$ |
| European G2 | $\begin{gathered} 0.03 \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.03 \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.05 \\ (0.06) \end{gathered}$ | $\begin{aligned} & -0.01 \\ & (0.05) \end{aligned}$ | $\begin{gathered} 0.03 \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.04 \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.03 \\ (0.07) \end{gathered}$ | $\begin{aligned} & -0.01 \\ & (0.05) \end{aligned}$ |
| European G3 | $\begin{gathered} 0.08 \\ (0.11) \end{gathered}$ | $\begin{gathered} 0.08 \\ (0.11) \end{gathered}$ | $\begin{gathered} 0.08 \\ (0.10) \end{gathered}$ | $\begin{gathered} 0.07 \\ (0.09) \end{gathered}$ | $\begin{gathered} 0.08 \\ (0.11) \end{gathered}$ | $\begin{gathered} 0.09 \\ (0.11) \end{gathered}$ | $\begin{gathered} 0.08 \\ (0.11) \end{gathered}$ | $\begin{gathered} 0.07 \\ (0.09) \end{gathered}$ |
| Demographic characteristics Age at interview | $\begin{gathered} 0.01 \\ (0.02) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.02) \end{gathered}$ | $\begin{gathered} 0.02 \\ (0.02) \end{gathered}$ | $\begin{gathered} 0.02 \\ (0.02) \end{gathered}$ | $\begin{gathered} 0.02 \\ (0.02) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.02) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.02) \end{gathered}$ | $\begin{gathered} 0.03 \\ (0.02) \end{gathered}$ |
| Age at interview squared | $\begin{aligned} & -0.01 \\ & (0.01) \end{aligned}$ | $\begin{aligned} & -0.01 \\ & (0.01) \end{aligned}$ | $\begin{aligned} & -0.01 \\ & (0.01) \end{aligned}$ | $\begin{aligned} & -0.01 \\ & (0.01) \end{aligned}$ | $\begin{gathered} -0.01 \\ (0.01) \end{gathered}$ | $\begin{gathered} -0.01 \\ (0.01) \end{gathered}$ | $\begin{aligned} & -0.01 \\ & (0.01) \end{aligned}$ | $\begin{aligned} & -0.01 \\ & (0.01) \end{aligned}$ |
| Interviewed during the covid pandemic (March 2020 and after) | $\begin{aligned} & -0.01 \\ & (0.06) \end{aligned}$ | $\begin{gathered} 0.01 \\ (0.05) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.05) \end{gathered}$ | $\begin{aligned} & -0.01 \\ & (0.04) \end{aligned}$ | $\begin{gathered} 0.01 \\ (0.06) \end{gathered}$ | $\begin{gathered} -0.01 \\ (0.06) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.06) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.04) \end{gathered}$ |
| Income terciles (ref. tercile 1) <br> Tercile 2 | $\begin{gathered} 0.06 \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.02 \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.21 * * * \\ (0.05) \end{gathered}$ | $\begin{gathered} 0.18 * * \\ (0.06) \end{gathered}$ | $\begin{gathered} 0.05 \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.04 \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.06 \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.11 \\ (0.06) \end{gathered}$ |
| Tercile 3 (top) | $\begin{gathered} 0.08 \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.04 \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.04 \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.06 \\ (0.05) \end{gathered}$ | $\begin{gathered} 0.09 \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.08 \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.08 \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.05) \end{gathered}$ |

[^3]Table A6 Continued

|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Structural mechanisms |  |  |  |  |  |  |  |  |
| Occupational closure |  | $\begin{gathered} -0.89 * * * \\ (0.23) \end{gathered}$ |  |  |  |  |  | $\begin{gathered} -1.12^{* * *} \\ (0.21) \end{gathered}$ |
| Vocational training |  |  | $\begin{gathered} -0.70 * * * \\ (0.05) \end{gathered}$ |  |  |  |  | $\begin{aligned} & -0.01 \\ & (0.06) \end{aligned}$ |
| Sorting into field of study (ref. Generic program) |  |  |  |  |  |  |  |  |
| Education, arts, and social sciences |  |  |  | $\begin{aligned} & -0.05 \\ & (0.03) \end{aligned}$ |  |  |  | $\begin{aligned} & -0.05 \\ & (0.04) \end{aligned}$ |
| Business, administration, and law |  |  |  | $\begin{gathered} -0.79 * * * \\ (0.05) \end{gathered}$ |  |  |  | $\begin{gathered} -0.75 * * * \\ (0.05) \end{gathered}$ |
| Natural sciences and communication |  |  |  | $\begin{gathered} -0.28 * * * \\ (0.06) \end{gathered}$ |  |  |  | $\begin{gathered} -0.23 * * * \\ (0.06) \end{gathered}$ |
| Engineering and agriculture |  |  |  | $\begin{gathered} -1.65 * * * \\ (0.04) \end{gathered}$ |  |  |  | $\begin{gathered} -1.62^{* * *} \\ (0.06) \end{gathered}$ |
| Health, welfare, and services |  |  |  | $\begin{gathered} -0.85 * * * \\ (0.11) \end{gathered}$ |  |  |  | $\begin{gathered} -0.76^{* * *} \\ (0.12) \end{gathered}$ |
| Individual-level mechanisms |  |  |  |  |  |  |  |  |
| Recent unemployment spells (last 5 years) |  |  |  |  | $\begin{gathered} 0.26^{* *} \\ (0.10) \end{gathered}$ |  |  | $\begin{aligned} & 0.16^{*} \\ & (0.07) \end{aligned}$ |
| School-to-work transition (ref. below 1 year) |  |  |  |  |  |  |  |  |
| 1 year to find a job |  |  |  |  |  | $\begin{gathered} 0.10 \\ (0.08) \end{gathered}$ |  | $\begin{gathered} 0.08 \\ (0.06) \end{gathered}$ |
| $2+$ years to find a job |  |  |  |  |  | $\begin{gathered} 0.22 * * \\ (0.07) \end{gathered}$ |  | $\begin{aligned} & 0.11^{*} \\ & (0.05) \end{aligned}$ |
| Belonging to a discriminated group |  |  |  |  |  |  | $\begin{gathered} 0.23 * * \\ (0.09) \end{gathered}$ | $\begin{gathered} 0.18 * * \\ (0.06) \end{gathered}$ |
| Constant | $\begin{gathered} -0.39 \\ (0.39) \end{gathered}$ | $\begin{aligned} & -0.37 \\ & (0.39) \end{aligned}$ | $\begin{aligned} & -0.30 \\ & (0.37) \end{aligned}$ | $\begin{gathered} 0.45 \\ (0.30) \end{gathered}$ | $\begin{gathered} -0.50 \\ (0.39) \end{gathered}$ | $\begin{gathered} -0.46 \\ (0.39) \end{gathered}$ | $\begin{aligned} & -0.40 \\ & (0.39) \end{aligned}$ | $\begin{gathered} 0.31 \\ (0.31) \end{gathered}$ |
| $\mathrm{R}^{2}$ | 0.01 | 0.03 | 0.12 | 0.38 | 0.02 | 0.02 | 0.02 | 0.41 |
| N | 6,563 | 6,563 | 6,563 | 6,563 | 6,563 | 6,563 | 6,563 | 6,563 |

[^4]Table A7 Weighted descriptive statistics of horizontal mismatch across fields of study, as well as of the percentage of males and females present in the fields of study across origin groups

|  | Avg <br> mismatch ${ }^{\text {a }}$ | Male |  |  | Female |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | non-Eu ${ }^{\text {b }}$ | Eu ${ }^{\text {c }}$ | Natives | non-EU ${ }^{\text {b }}$ | EU ${ }^{\text {c }}$ | Natives |
| Field of study |  |  |  |  |  |  |  |
| Generic program and qualifications | 0.96 | 10 | 7 | 4 | 7 | 6 | 6 |
| Natural sciences, mathematics, and statistics | 0.95 | 6 | 5 | 5 | 5 | 5 | 30 |
| Social sciences, journalism, and information | 0.82 | 6 | 5 | 3 | 7 | 6 | 6 |
| Arts and humanities | 0.77 | 6 | 3 | 3 | 10 | 10 | 10 |
| Services | 0.69 | 4 | 4 | 7 | 6 | 11 | 8 |
| Teaching | 0.66 | 1 | 1 | 1 | 2 | 3 | 3 |
| Information and communication technologies | 0.43 | 7 | 3 | 3 | 2 | 1 | 1 |
| Agriculture | 0.37 | 1 | 4 | 7 | 1 | 1 | 1 |
| Business, administration, and law | -0.20 | 20 | 16 | 14 | 38 | 32 | 34 |
| Engineering, manufacturing, and construction | -0.58 | 34 | 47 | 48 | 7 | 8 | 7 |
| Health and welfare | -0.65 | 4 | 4 | 5 | 15 | 17 | 20 |

Notes: The first column presents the average horizontal mismatch in each field of study. The subsequent columns present the percentage of individuals in each field of study within origin groups. G1, G2, and G3 are pooled. Data are from authors' calculations.
${ }^{\text {a }}$ Our measure of horizontal mismatch is z -standardized. Higher values indicate higher than average mismatch in the field of study. Lower values indicate lower than average mismatch in the field of study.
${ }^{\mathrm{b}}$ non-EU is short for non-European.
${ }^{\mathrm{c}} \mathrm{EU}$ is short for European.

Table A8 Weighted coefficients from OLS regressions estimating vertical and horizontal mismatch across generations and origin groups, excluding generic programs and qualifications

|  | Vertical |  |  | Horizontal |  |
| :--- | :---: | :---: | :---: | :---: | :---: |
|  | Male | Female |  | Male | Female |
| Generations and origin groups <br> (ref. natives G4+) |  |  |  |  |  |
| non-European G1 | $0.42^{* * *}$ | $0.41^{* * *}$ |  | $0.24^{* * *}$ | $0.19^{* * *}$ |
|  | $(0.05)$ | $(0.06)$ |  | $(0.06)$ | $(0.06)$ |
| non-European G2 | -0.05 | 0.02 |  | $0.22^{* * *}$ | -0.06 |
|  | $(0.07)$ | $(0.06)$ |  | $(0.07)$ | $(0.06)$ |
| non-European G3 | -0.18 | 0.12 |  | $0.36^{*}$ | 0.20 |
|  | $(0.16)$ | $(0.14)$ |  | $(0.15)$ | $(0.12)$ |
| European G1 | $0.27^{* * *}$ | $0.35^{* * *}$ |  | 0.07 | $0.17 * *$ |
|  | $(0.06)$ | $(0.06)$ |  | $(0.07)$ | $(0.06)$ |
| European G2 | -0.05 | -0.06 |  | 0.03 | -0.07 |
|  | $(0.07)$ | $(0.06)$ |  | $(0.07)$ | $(0.07)$ |
| European G3 | -0.02 | 0.16 |  | 0.05 | 0.15 |
|  | $(0.10)$ | $(0.08)$ |  | $(0.11)$ | $(0.10)$ |
| Demographic characteristics |  |  |  |  |  |
| Age at interview | 0.01 | 0.03 |  | 0.03 | 0.01 |
|  | $(0.02)$ | $(0.02)$ |  | $(0.02)$ | $(0.02)$ |
| Age at interview squared | -0.01 | $-0.01^{*}$ |  | -0.01 | 0.01 |
|  | $(0.01)$ | $(0.01)$ |  | $(0.01)$ | $(0.01)$ |
| Interviewed during the covid | 0.03 | -0.01 |  | 0.01 | -0.01 |
| pandemic (March 2020 and after) | $(0.06)$ | $(0.05)$ |  | $(0.06)$ | $(0.05)$ |
| Income terciles (ref. tercile 1) |  |  |  |  |  |
| Tercile 2 | -0.05 | -0.02 |  | 0.07 | -0.01 |
|  | $(0.06)$ | $(0.06)$ |  | $(0.07)$ | $(0.06)$ |
| Tercile 3 (top) | -0.10 | $-0.17^{* *}$ |  | 0.10 | $-0.24^{* * *}$ |
| Constant | $(0.06)$ | $(0.07)$ |  | $(0.07)$ | $(0.08)$ |
|  | 0.48 | 0.03 |  | -0.70 | -0.15 |
| R | $(0.37)$ | $(0.40)$ |  | $(0.41)$ | $(0.40)$ |
| N | 0.10 | 0.08 |  | 0.01 | 0.02 |

Notes: Robust standard errors at the individual level in parentheses. Data are from authors' calculations.

* p < . 05 ; ** p < . $01 ;$ *** p < . 001

Table A9 Weighted coefficients from OLS regressions estimating vertical and horizontal mismatch across generations and origin groups, excluding small occupations ${ }^{\text {a }}$

|  | Vertical |  | Horizontal |  |
| :---: | :---: | :---: | :---: | :---: |
|  | Male | Female | Male | Female |
| Generations and origin groups (ref. natives G4+) |  |  |  |  |
| non-European G1 | $\begin{gathered} 0.30^{* * *} \\ (0.05) \end{gathered}$ | $\begin{gathered} 0.37 * * * \\ (0.05) \end{gathered}$ | $\begin{gathered} 0.29^{* * *} \\ (0.05) \end{gathered}$ | $\begin{gathered} 0.21^{* * *} \\ (0.05) \end{gathered}$ |
| non-European G2 | $\begin{aligned} & -0.12 \\ & (0.07) \end{aligned}$ | $\begin{gathered} 0.02 \\ (0.06) \end{gathered}$ | $\begin{gathered} 0.24 * * * \\ (0.07) \end{gathered}$ | $\begin{aligned} & -0.05 \\ & (0.06) \end{aligned}$ |
| non-European G3 | $\begin{gathered} -0.27 \\ (0.16) \end{gathered}$ | $\begin{gathered} 0.14 \\ (0.14) \end{gathered}$ | $\begin{gathered} 0.43 * * * \\ (0.13) \end{gathered}$ | $\begin{gathered} 0.18 \\ (0.11) \end{gathered}$ |
| European G1 | $\begin{aligned} & 0.17 * \\ & (0.07) \end{aligned}$ | $\begin{gathered} 0.36 * * * \\ (0.06) \end{gathered}$ | $\begin{aligned} & 0.15^{*} \\ & (0.07) \end{aligned}$ | $\begin{gathered} 0.16 * * \\ (0.06) \end{gathered}$ |
| European G2 | $\begin{gathered} -0.06 \\ (0.06) \end{gathered}$ | $\begin{aligned} & -0.03 \\ & (0.06) \end{aligned}$ | $\begin{gathered} 0.02 \\ (0.07) \end{gathered}$ | $\begin{gathered} -0.08 \\ (0.06) \end{gathered}$ |
| European G3 | $\begin{aligned} & -0.06 \\ & (0.11) \end{aligned}$ | $\begin{gathered} 0.17 \\ (0.09) \end{gathered}$ | $\begin{gathered} 0.08 \\ (0.11) \end{gathered}$ | $\begin{gathered} 0.15 \\ (0.09) \end{gathered}$ |
| Demographic characteristics |  |  |  |  |
| Age at interview | $\begin{gathered} 0.03 \\ (0.02) \end{gathered}$ | $\begin{gathered} 0.06^{* *} \\ (0.02) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.02) \end{gathered}$ | $\begin{aligned} & -0.01 \\ & (0.02) \end{aligned}$ |
| Age at interview squared | $\begin{gathered} -0.01 * * \\ (0.01) \end{gathered}$ | $\begin{gathered} -0.01 * * * \\ (0.01) \end{gathered}$ | $\begin{aligned} & -0.01 \\ & (0.01) \end{aligned}$ | $\begin{gathered} 0.01 \\ (0.01) \end{gathered}$ |
| Interviewed during the covid pandemic (March 2020 and after) | $\begin{gathered} 0.04 \\ (0.06) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.05) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.06) \end{gathered}$ | $\begin{aligned} & -0.03 \\ & (0.05) \end{aligned}$ |
| Income terciles (ref. tercile 1) |  |  |  |  |
| Tercile 2 | $\begin{aligned} & -0.04 \\ & (0.06) \end{aligned}$ | $\begin{aligned} & -0.03 \\ & (0.06) \end{aligned}$ | $\begin{gathered} 0.06 \\ (0.07) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.06) \end{gathered}$ |
| Tercile 3 (top) | $\begin{gathered} -0.08 \\ (0.06) \end{gathered}$ | $\begin{aligned} & -0.10 \\ & (0.07) \end{aligned}$ | $\begin{gathered} 0.08 \\ (0.07) \end{gathered}$ | $\begin{gathered} -0.27 * * * \\ (0.07) \end{gathered}$ |
| Constant | $\begin{gathered} 0.09 \\ (0.38) \end{gathered}$ | $\begin{aligned} & -0.59 \\ & (0.42) \end{aligned}$ | $\begin{aligned} & -0.40 \\ & (0.40) \end{aligned}$ | $\begin{gathered} 0.18 \\ (0.38) \end{gathered}$ |
| $\mathrm{R}^{2}$ | 0.10 | 0.08 | 0.01 | 0.03 |
| N | 6,529 | 6,391 | 6,529 | 6,391 |

Notes: Robust standard errors at the individual level in parentheses. Data are from authors' calculations.
${ }^{\text {a }}$ Small occupations refer to occupations with fewer than 5,000 individuals in the French Labor Force survey.

* $\mathrm{p}<.05 ; * * \mathrm{p}<.01 ; * * * \mathrm{p}<.001$


Figure A1 Weighted coefficients from OLS regressions estimating vertical mismatch among G1, differentiating between those who hold a French and a foreign degree. Natives are the reference group (indicated by the vertical line). Vertical mismatch is operationalized using information on the standardized ridit. Values above zero for standardized ridits indicate overeducation, while values below zero indicate under-education. The model controls for age at interview, age at interview squared, an indicator variable of whether the individual was interviewed during the covid pandemic (March 2020 and after), and income terciles.


[^0]:    ${ }^{1}$ We use the term "natives" to designate people born in France to French-born parents. For sake of clarity and in line with previous work, we make a distinction between descendants of immigrants and natives, while acknowledging that immigrants' descendants are also born in France.

[^1]:    Continued

[^2]:    Notes: Data are from authors' calculations.
    ${ }^{\mathrm{a}}$ Income refers to wages in 2020 for employed individuals and CEOs.

[^3]:    Continued

[^4]:    Notes: Robust standard errors at the individual level in parentheses. Data are from authors' calculations.

    * p < . 05 ; ** p < . 01 ; *** p < . 001

