

Spatial mobility and overeducation of young workers: New evidence from France

Florian Fouquet, Florent Sari

▶ To cite this version:

Florian Fouquet, Florent Sari. Spatial mobility and overeducation of young workers: New evidence from France. Papers in Regional Science, 2023, 102 (5), pp.945-983. 10.1111/pirs.12755. hal-04086383v2

HAL Id: hal-04086383 https://hal.science/hal-04086383v2

Submitted on 11 Sep 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers. L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



DOI: 10.1111/pirs.12755

FULL ARTICLE



Check for updates

Spatial mobility and overeducation of young workers: New evidence from France

Florian Fouquet 1,2 | Florent Sari 3 |

¹LEMNA, Nantes Université, Nantes, France ²GAINS, Le Mans Université, Le Mans, France ³ERUDITE, TEPP et CEET, Université Paris-Est Créteil, Créteil, France

Correspondence

Florian Fouquet, IAE Nantes – Economie & Management, Chemin de la Censive du Tertre, Nantes Cedex 3, France.

Email: florian.fouquet@univ-nantes.fr

Abstract

This paper explores the influence of spatial mobility on the risk of overeducation of French young workers. Mobilizing a survey following a cohort of young graduates entering the labour market from 2010 until 2013, our results reveal that interregional migration decreases the risk of (statistical and subjective) overeducation. We also evidence that migration to an economic centre (the Paris region) has an even stronger negative effect and that more educated workers benefit more from spatial mobility. These results are robust to controlling for self-selection and the endogeneity of migration, as well as to various specifications of the model.

KEYWORDS

educational mismatch, employment, instrumental variables approach, overeducation, spatial mobility

JEL CLASSIFICATION C35, J24, R23

1 | INTRODUCTION

Most job seekers are searching for jobs in local labour markets, around their residential location. However, smaller markets often mean fewer suitable job opportunities. If there is no adequate job available in the area, an individual has three options (Simpson, 1992). The first is to remain unemployed. The second is to accept a job requiring less education than the individual actually has, i.e. become overeducated. To avoid both unemployment and overeducation, the third option is to search for jobs located farther from them. The economic literature has indeed shown that spatial mobility tends to reduce the risk of unemployment as it permits access to new areas with better job opportunities (see, for instance, the works of Pissarides & McMaster, 1990; Détang-Dessendre, 1999; Fahr & Sunde, 2006; Rupert & Wasmer, 2012; Langella & Manning, 2022). A recent work by Schmutz et al. (2021) confirms



that this is especially true for the most educated workers. While the links between spatial or geographical mobility and unemployment have been the subject of numerous empirical analyses, this is not the case concerning the links with overeducation. This phenomenon, which particularly concerns the most educated young workers, remains somewhat understudied.

In France, as in many OECD countries, young graduates entering the labour market experience important issues in their early professional careers. Firstly, they face a higher risk of unemployment. In 2021, 19.6% of the 15–24 years old in the labour force were unemployed. Secondly, they also face a higher risk of overeducation (Dolton & Vignoles, 2000). However, being overeducated at the beginning of the career has a detrimental impact on future labour market outcomes (Baert et al., 2013; Baert & Verhaest, 2019) due to the negative signal of overeducation and the decline of skills over time. Then, it is essential for young workers to access a matched job as soon as possible after their graduation. In this context, broadening their job search area may be a strategy for these young workers to avoid overeducation and its scarring effects. In the French case, although young graduates generally tend to stay in the same region for higher education and employment, their share has declined over the past few decades (Bernela & Bonnal, 2022), the spatial mobility allowing them to increase chances to find suitable and better-paid jobs (Lemistre & Moreau, 2009).

In this work, we contribute to the existing literature by investigating the consequences of spatial mobility for young workers in their early careers. In particular, we examine the links between geographical mobility (between graduation and the job currently occupied) and the risk of overeducation, the latter being defined as the fact of occupying a job requiring an educational level lower than one's own. Previous works have indeed shown that expanding the job search area could be an important factor in avoiding overeducation in OECD countries (see Büchel & van Ham, 2003, for Germany; Hensen et al., 2009, for the Netherlands; Devillanova, 2013, for Italy; or even Romaní et al., 2016, for Spain). However, to our knowledge, such a question has not been studied yet in the French context. There is previous evidence of a negative effect of residential migration on the risk of unemployment, especially for highly educated workers (Détang-Dessendre, 1999; Détang-Dessendre et al., 2004). Still, Bernela and Bonnal (2022) showed that French young workers were not spatially mobile, with less than 30% relocating after graduation, even though the most educated are more likely to move, especially, to bigger cities with more labour market prospects (Détang-Dessendre et al., 2004). Therefore, we document the differentiated effects of spatial mobility on overeducation depending on the destination of the residential migration: in addition to the analysis of interregional migrations nationwide, we make a specific focus on migrations to the Paris region. Although Paris is not the only economic centre in France, it accounts for 20% of the country's labour force and concentrates a large pool of job opportunities and higher wages (Combes et al., 2015). Similar geographical structures can be observed in other countries (see Andersson et al., 2014, for Sweden; Faggian & McCann, 2008, for the UK; or Venhorst et al., 2010, for the Netherlands). Previous studies showed a negative effect of migration towards economic centres on overeducation (lammarino & Marinelli, 2015), but, overall, the effects of residential migration remain dependent on the characteristics of the destination region (Devillanova, 2013; Jauhiainen, 2011). However, Venhorst et al. (2010) evidenced significant migration flows between peripheral regions in the Netherlands, which remained attractive even for highly educated workers.

To examine the relationship between spatial mobility and the risk of overeducation, we use the Génération 2010 survey from the Céreq (Centre d'études et de recherche sur les qualifications, French Center for Studies and Research on Qualifications), following a cohort of French young people who left the educational system from 2010 through 2013. Because the survey provides information on residential mobility, it is used to check if a regional migration since graduation is a way to avoid overeducation. The empirical design retained to analyse the relationship between migration and overeducation combines three econometric models. The first one is to account for the sample selection problem, as overeducation is observable only for individuals who actually work. The second one is for the endogeneity of the migration decision. Indeed, there may be some unobserved factors simultaneously

determining migration and overeducation, or some reverse causality, as overeducation might affect the migration decision. For these reasons, we run instrumental variable estimations, in which the migration decision is instrumented by migrations and stays abroad observed during past education. The last equation is for testing the relationship between the migration decision and the risk of overeducation in the labour market. This econometric strategy should allow us to better identify the causal effect of spatial mobility (or migration) on overeducation.

Our approach is original for at least three reasons. Firstly, if there are already some works investigating the role of migration and the implications for education–job matching issues, there is none available for France. This work represents a particularly interesting study case as the Paris region polarizes a significant proportion of jobs and workers. In this context, migration to Paris may have differentiated effects compared to migration to other regions. We try to disentangle these questions by examining all migrations between regions and those related only to the Paris region. Secondly, our work is based on a representative sample of the stock of both short-cycle higher education and long-cycle higher education graduates. By studying these different populations, we want to check if migration is more favourable for the most educated profiles. Combes et al. (2012) have indeed shown that the relocation of workers between French local labour markets may differ based on their skills. Thirdly, our data enable us to use two measures of overeducation, a statistical measure and a subjective one. More specifically, the statistical measure is based on statistical characteristics of the distribution of education for each occupation, while the subjective one is based on workers' self-assessments about the skills required to do their jobs. We can, therefore, explore the actual situation of overeducation and the feeling of being overeducated, respectively.

The main results are as follows. Firstly, we find that having migrated (i.e. change of region) between the last degree obtained and the job currently held tends to decrease the probability of being overeducated. It is confirmed for both of our measures of overeducation, the statistical and the subjective ones. Considering self-selection into employment and the endogeneity of the migration decision does not change conclusions for the statistical measure but makes the effect observed for the subjective one significant. Secondly, when we focus on the migration to Paris, we evidence an even stronger negative effect on the risk of overeducation, confirming the advantage of such a region in terms of job opportunities. Finally, we show that the benefits of migration may differ based on the educational level of young workers. In fact, no effect is found for individuals with a 2-year degree, while migration is particularly 'advantageous' for those with a 3- or 4-year degree. In comparison, individuals with at least a 5-year degree also decrease their risk of being overeducated with spatial mobility, but the effect is smaller than that for the previous group.

Section 2 offers a description of the theoretical links between the migration decision and overeducation and a literature review of the previous empirical works exploring this question. Section 3 presents the data and variables retained for our analysis. Section 4 provides some descriptive statistics of our study sample. Section 5 describes the estimation strategy, and Section 6 displays the results of our estimations. Section 7 concludes.

2 | SPATIAL MOBILITY AND OVEREDUCATION

2.1 | Theoretical links

Individuals working in occupations for which they have more education than what is required are considered over-educated. This phenomenon is known to particularly affect young workers entering the labour market (Dolton & Vignoles, 2000). Theoretically, the career mobility theory (Sicherman & Galor, 1990) exposes overeducation as a temporary phenomenon, where workers accept a job requiring less education than they actually have to improve future outcomes on the labour market. Baert et al. (2013) challenge this conclusion by showing that being overeducated at the beginning of a career is detrimental to future labour market positions. Moreover, in the short term, overeducated workers have lower wages (Verdugo & Verdugo, 1989) and lower satisfaction at work (Tsang et al., 1991) than individuals with the same level of education but working in a matched occupation. Therefore,



extending their geographic mobility may be a strategy for these individuals to avoid overeducation and its scarring effects, as in the theory of Simpson (1992).

Concretely, it is expected that the risk of overeducation is higher for the workers who are restricted to a smaller local labour market. In such places, the lower density of suitable job opportunities is likely to hinder the job search process and the matching quality between workers and job vacancies. As a consequence, spatial mobility can be seen as a way of avoiding overeducation because it provides access to more job opportunities. Some previous works have indeed found that geographic mobility positively influences workers' labour market positions (Büchel & Battu, 2003; Hensen et al., 2009; van Ham, 2001).

In this work, we start from this assumption, and we hypothesize that geographically mobile graduates have a lower probability of being overeducated compared to those who are less mobile. With our data, we are able to see if French young workers have changed their region of residence between the last degree obtained and the moment when they are interrogated for the survey (3 years later). We believe that those who make the decision to move between the two dates are less likely to be overeducated. The mobility decision is indeed based on arbitrage between the costs and benefits associated with it. Because the costs of mobility may be high (due to financial and psychological costs), the job occupied must offer good working conditions. That is to say, it has to be matched to the worker's skills, and the wage offered should partially or fully offset the costs associated with the mobility decision. To the extent that job opportunities are richer in the Paris region than in other regions, we assume that the probability of finding a well-suited job is higher in this region and then that the risk of overeducation should be lower.

In addition, it has been shown that spatial mobilities or migrations are more frequent for the most skilled people (Combes et al., 2012). Starting from this fact, if we consider different groups of young workers with different behaviours related to migration (i.e. the highly skilled workers who have a high propensity to migrate and the skilled workers who do it less frequently), some differentiated effects on the probability of being overeducated might be observed. We can indeed consider that the expected benefits of migration are higher for those who are less likely to adopt such behaviour. Indeed, if the decision to migrate has been taken, it is theoretically to obtain a job corresponding to the skills offered. Concerning the workers for whom these mobilities are frequent, the expected benefits could be lower. We try to disentangle these questions by considering the short- and long-cycle higher education graduates separately.

Finally, the links between spatial mobility and overeducation are likely to be different between men and women. Frank (1978) argues that, in a couple, the husband is looking for a job in the global labour market, whereas the wife is looking only in the local labour market where her partner has obtained a job. Then, we can expect that women in a couple are more likely to be overeducated due to a smaller job search area. Büchel and Battu (2003) confirm this hypothesis as they show that the probability of being overeducated is higher for married women living in rural areas. The size of the local labour market or access to other labour markets through some mobilities can help them find a suitable job. However, when marital status is taken into account, Büchel and van Ham (2003) provide evidence that women experience a penalty in their chances of finding a job but are not more prone to overeducation than men. The authors also argue that gender differences in household roles may be important in influencing women to accept job offers closer to home. If there are children in the household, women are more likely to be restricted in their spatial mobility. On this point, empirical evidence is mixed: some authors do not find any significant effect on overeducation for women having children (Devillanova, 2013; Ramos & Sanromá, 2013), while some others observe a positive one (Büchel & van Ham, 2003) or even a negative one (Jauhiainen, 2011).

2.2 | Literature review

In recent decades, several studies have examined the connections between spatial mobility and the risk of overeducation, with a primary focus on local labour markets in OECD countries, particularly concerning young individuals with higher education. However, two main issues need to be addressed to establish a clear causal relationship between the decision to move and overeducation. The first one is a possible 'selection bias' because overeducation is observable only among graduates who are currently employed. The second one is the endogeneity of the mobility decision. There might be unobserved characteristics influencing both the mobility behaviour and the likelihood of being overeducated. While the pioneering studies may not have adequately considered these biases, more recent ones have made attempts to address them. However, identifying suitable instrumental variables to tackle these issues remains challenging.

Büchel and van Ham (2003) were among the first to highlight the role of regional labour market size (determined by the ability to search far away from the place of residence) as a potential explanatory variable of overeducation. Based on German data, the authors find that this risk decreases with individual spatial mobility and increases with the time needed to travel to a large agglomeration. They confirm that the size of the labour market is an important factor in avoiding overeducation. However, a limitation arises when the authors take into account self-selection into employment through a bivariate probit model. In doing so, they fail to consider the endogenous relationship between the mobility decision and overeducation, which could potentially bias their results. Using Dutch data, Hensen et al. (2009) investigate the relationship between spatial mobility and education–job mismatch. Although they do not address the two problems mentioned earlier, they found that being more mobile reduces vertical educational mismatches (i.e. when the worker's level of education is higher than what is required for their employment) but increases horizontal educational mismatches (i.e. when the worker's field of education is different from the mode field for their occupation). In other words, the risk of being overeducated is lower for spatially flexible workers, but they are more often employed in jobs outside their field of study.

Jauhiainen (2011) also investigates the influence of mobility on the risk of overeducation in Finnish regional labour markets. Using a probit model that controls for selection bias (the Heckman two-step method), she finds an ambiguous effect of spatial mobility on the probability of being overeducated. Specifically, the study reveals that moving to another region has a negative impact on the likelihood of being overeducated, while moving within the same region has a positive effect. This finding is consistent with the idea of limited spatial flexibility, increasing overeducation risk. Employing a similar methodology, Ramos and Sanromá (2013) examine the influence of local characteristics and spatial mobility on overeducation in Spanish local labour markets. Their results were consistent with previous findings, demonstrating that the size of local labour markets and the opportunity to expand job search areas (via commuting) are relevant factors that reduce the risk of overeducation.

Devillanova (2013) goes a step further by proposing an analysis that simultaneously considers self-selection and the endogeneity of migration. The results of this study indicate a negative correlation between short-distance mobility and the probability of Italians being overeducated, but they do not reveal a clear relationship for internal migration. As a result, the author concludes that the links between migration and overeducation remain uncertain, emphasizing the need for further research to better identify the underlying effects. Other researchers have also focused on the Italian local labour markets. For instance, Croce and Ghignoni (2015) tend to confirm the relevance of spatial mobility as an explanatory factor for the individual risk of educational mismatch. In line with Devillanova (2013), they control for self-selection into employment and test for the endogeneity of spatial mobility. However, their results differ somewhat from the previous findings, as they reveal a negative effect on both commuting time (short-distance mobility) and migration. Interestingly, the effects differ based on the educational level: commuting is favourable for upper-secondary graduates, while migration is more beneficial for university graduates.

lammarino and Marinelli (2015) study the determinants of education–job mismatches among recent university graduates in Italy, with a particular focus on the role of inter-regional migration. By controlling for both the endogenous relationship between migration and employment and the self-selection bias, they find that while migration at the national level decreases the probability of overeducation, significant differences emerge when considering the subnational dimension. In the French context, our goal is to identify similar relationships by distinguishing between Paris and other regions concerning migration. Moving on to another study, Meliciani and Radicchia (2016) specifically investigate the role of informal recruitment channels on the risk of being overeducated, while also considering its impact on spatial mobility. They estimate different equations which allow them to control for selection into



employment and a likely endogeneity bias for mobility decisions. The main finding indicates that using an informal channel has a positive effect on the risk of overeducation and a negative effect on migration. Another important result is that migration may reduce the risk of overeducation, although this finding is applicable only to specific geographical areas of the Italian territory, consistent with the work of lammarino and Marinelli (2015).

Some recent papers explore spatial mobility at different levels. For instance, Di Paolo et al. (2017) examine mobility at a local level, focusing on the effect of job accessibility on job-education mismatch in the metropolitan area of Barcelona. Their findings, obtained from a joint model for car ownership, employment selectivity and mismatch, confirm that having access to private vehicles reduces the risk of job-education mismatch. In addition, they reveal that public transport job accessibility directly influences this mismatch problem. Venhorst and Cörvers (2018) estimate the impact of internal migration on job-match quality for university and college graduates in the Netherlands. Using an instrumental variables approach to control for self-selection biases among migrants, they find a positive effect of migration on the likelihood of achieving a vertical education match and giving positive subjective evaluations of job-match quality. However, no significant effect is evidenced on the likelihood of achieving a horizontal match. Most recently, Ghosh and Grassi (2020) evaluated the effects of international mobility on the education-job mismatch of Italian PhD graduates. By controlling for self-selection into cross-border mobility, they highlight that migration to foreign countries significantly reduces the risk of overeducation.

The various studies reveal contrasting effects depending on the scale of spatial mobility considered. The effects of migration on the risk of overeducation are generally significant for long distances within a country or for international migrations. At the country level, migrations to some specific regions may be favourable, while they may be unfavourable for others. These effects also depend on individual characteristics. For instance, migration is likely to be more beneficial for certain levels of education. This research contributes to the existing literature by examining, in the context of France, the relationships between inter-regional mobility and job-education mismatch and by distinguishing individuals based on their education levels.

3 | DATA AND VARIABLES

3.1 | Data

This work is based on data from the Génération 2010 survey conducted by Céreq in spring 2013. The survey captures the entry into and trajectories during the first year in the French labour market of 33,547 individuals who left school for the first time between October 2009 and October 2010. Random sampling was employed to ensure the representativeness of the data at the regional level and for each educational level. The data provide socio-demographic information about individuals (gender, age and cohabitation status) and detailed information about their education (highest degree obtained and field of study). Furthermore, the survey includes information about the successive labour market positions (occupation, firm size and business sector) of these individuals from their graduation to the time they were surveyed.

The focus of this study is on higher education graduates. Workers with lower education are less likely to be overeducated, and, in some cases, it is not even possible to be overeducated for the lowest degrees. The sample is divided into three levels of education based on the number of years of study after the baccalaureate: the 2-year university graduates, the 3- and 4-year university graduates and the long-cycle higher education graduates who have studied for 5 years or more. Self-employed workers are excluded from the sample. After these restrictions, our final sample consists of 15,865 individuals who were surveyed between 28 and 45 months after their graduation. The study focuses on the labour market position at the time of the survey because it is the only time point for which information about the place of residence is available, which is needed to determine spatial mobility. In addition, some other variables, such as cohabitation status, are observed only at the time of the survey.

Focusing on higher education graduates in the first 3 years after graduation is not a trivial choice. It ensures a fairly homogenous sample, especially in terms of professional experience, which may have a negative effect on overeducation through job changes after some time (Rubb, 2003). Moreover, all individuals graduated in a short time window; they thus experienced similar economic conditions when entering the labour market (Croce & Ghignoni, 2012). Because they face higher risks of overeducation (Dolton & Vignoles, 2000) and less favourable labour market prospects in general (Bell & Blanchflower, 2011; Blanchflower & Freeman, 2000), young workers are also of particular interest for targeted public policies. Furthermore, even though observing migration only in the first years after graduation has some limitations (Greenwood, 1997), policies to support mobility may be more adapted for younger workers, because they have lower mobility costs (less likely to have children, more often tenants, etc.). In addition, in the French context, young students do not necessarily have to move to access higher education: almost all fields of study are available in all regions, with universities accessible with only short mobilities. Because the propensity to relocate is related to past migration (DaVanzo & Morrison, 1981), young workers entering the labour market may not engage in spatial mobility without incentives. The findings of Bernela and Bonnal (2022) somehow confirm this idea, showing that migration between graduation and employment was increasing over time but remained quite rare. Nevertheless, previous works showed that higher-skilled workers were more likely to relocate (Combes et al., 2012; Greenwood, 1997), especially for job-related reasons (Détang-Dessendre et al., 2004). For this specific demographic group, residential migration might also be a necessity because highly educated jobs are not available everywhere but rather tend to be concentrated in specific areas (Détang-Dessendre, 1999).

3.2 | Variables

3.2.1 | Dependent variable: The risk of overeducation

In this work, we are interested in the risk of overeducation among young graduates. The existing literature offers three main approaches to measuring this phenomenon:

- 1. *Objective measures*: This method defines what should be considered the 'normal' match between education and occupations, based on the skills required for each occupation (Rumberger, 1981).
- 2. Subjective measures: This method is based on workers' self-assessments regarding the degree they believe is required to do or to get their job (Duncan & Hoffman, 1981).
- 3. Statistical measures: It relies on the statistical characteristics of the education distribution for each occupation, such as the mean (Verdugo & Verdugo, 1989) or the mode (Croce & Ghignoni, 2012; Davia et al., 2017).

Our dataset enables us to employ two different measures of mismatch. We can use the subjective and the statistical ones. Therefore, we can explore the feeling of being overeducated and the actual situation of overeducation, respectively.

Regarding the subjective measure, respondents are asked in the Génération survey if they are employed above, below or at their skill level.² However, it is important to note that the answer to this question may reflect skill mismatch, i.e. overskilling, rather than educational mismatch, i.e. overeducation. Overskilling refers to the underutilization of the skills possessed by workers, while overeducation refers to the difference between the level of schooling they have acquired and the level required for the job they currently occupy. It has been shown by Allen and van der Velden (2001) that these two dimensions of mismatch do not overlap systematically. Therefore, it becomes quite complicated to precisely determine which dimension respondents consider when answering the survey. To avoid any

²The following question is asked: 'About this job, would you say you are used: At your skill level (1); below your skill level (2); above your skill level (3)?'.



confusion, in this study, we will refer to subjective mismatch. Individuals will be considered subjectively mismatched if they indicate that they are employed below their level of skills. In this case, our dependent variable takes the value 1 and 0 otherwise.

There is no ambiguity between overeducation and overskilling when using the statistical measure. We mobilize a bimodal measure, where individuals are considered statistically overeducated if their educational level is above the higher of the two most common levels required for their specific occupation. By retaining two modes instead of one, we account for the wide range of educational levels in consideration and the need to ensure a sufficiently large sample size within occupational groups. To determine what degrees are considered 'normal' for each occupation, we do not limit ourselves to the sample of young workers. This decision is made to avoid potential alterations in the distribution of education by occupation because younger workers are more likely to experience overeducation compared to older workers. Therefore, we mobilize the 2013 French Labour Force Survey (Enquête Emploi) from Institut National de la Statistique et des Études Économiques (Insee), which corresponds to the year when respondents were surveyed for Génération 2010. This dataset provides information on workers of all age groups, including educational levels and occupations at a detailed level, enabling us to establish a precise correspondence between them. The classifications of educational and occupational levels, as well as the aforementioned education–occupation correspondence, are reported in Tables A1–A3 in Appendix A.

3.2.2 | Independent variables

The Génération 2010 survey provides us a large set of explanatory variables about individuals' socio-economic characteristics, education and labour market positions. To explain the risk of educational mismatch, we gather information about young graduates and the jobs they occupy.

Regarding individual characteristics, we take into account gender and age at the time of graduation. In addition, we create binary variables to indicate whether individuals live with a partner or with their parents (the reference being 'living alone') and whether they have children. Having children is also associated with the fact of being a woman. It is a way to check to what extent household configuration matters. In particular, women who are primarily concerned with their children may restrict their spatial horizon of job search and be more often overeducated. To analyse the effects of education and the field of study, we create dummy variables. It is worth noting that graduating in certain fields may lead to a higher risk of mismatches compared to others (Meroni & Vera-Toscano, 2017). As for the educational level, the impact on overeducation remains theoretically ambiguous. On the one hand, having a higher degree may indicate higher skills and knowledge, offering some level of protection against overeducation. On the other hand, higher degrees may exceed the standard requirements for a larger proportion of occupations, resulting in more frequent instances of mismatches.

Regarding the labour market position of the individuals, we incorporate information about the employer and job characteristics. Firstly, we include dummies for the sector of the firm because there may be more instances of overeducation in some sectors compared to others (Nauze-Fichet & Tomasini, 2002). Secondly, we introduce dummies to account for full-time work and permanent jobs. Young workers might be less selective when considering temporary jobs compared to permanent positions. Consequently, they may accept a job for which they are overeducated if they perceive it as a transitional position. This is what would predict the career mobility theory (Sicherman & Galor, 1990). We also include the time spent (in months) between graduation and the first job held for each individual. Because it provides information on the duration of a job search, it can be argued that a longer period of time is more likely to lead to a suitable job.

In this work, we argue that one of the main factors determining the risk of overeducation is the spatial mobility of graduates. By examining the regions where young people have obtained their last degree and where they actually live at the time of the survey, we are able to determine if they have known spatial mobility. Concretely, we create a dummy variable taking the value 1 if the graduate has changed the region between their last degree and the region

where they live 3 years later, and 0 otherwise. First of all, we consider all inter-regional migrations, whatever the region of arrival of the migrants. Then, we focus on migrations to the Paris region exclusively. Because it is a region that polarizes a large part of job opportunities and workers and that concentrates high levels of wages and qualifications (Combes et al., 2015), we believe that it must be distinguished from other regions. We retain an administrative definition of French regions.³ Its geography is presented in Figure B1 in Appendix B.

4 | DESCRIPTIVE STATISTICS

We provide descriptive statistics about our sample in Table 1. Firstly, we observe that there are slightly more women (56%) than men in our sample. About half of the individuals live with a partner, and more than 30% live alone. The rest of the individuals still live with their parents at the time of the survey. A large majority of individuals in the sample do not have children. It is not surprising as it represents young people who have recently completed their studies. We do not consider the number of children because the vast majority of households have only one child (approximately 80% of the total).

Concerning educational levels, 3- and 4-year degrees are underrepresented in comparison with both shorter and longer tertiary degrees. This can be explained by the purpose of these degrees: 3- and 4-year degrees are transitory levels, designed to give access to longer studies. On the contrary, 2- and 5-year degrees are supposed to allow direct integration into the labour market. All fields of study are represented in the same proportions, with the exception of agriculture (underrepresented) and health (overrepresented).

Three years after graduation, 81.7% of the individuals were employed. Services and public sector workers represent a large share of our sample (more than 75%). Concerning the job characteristics, a majority of the individuals are working full time (more than 85%), but it must be noted that about a third of our sample have temporary contracts. It is a rather high proportion of temporary contracts for workers in the French labour market.⁴ However, young people are generally confronted with this kind of job due to their lack of experience when they leave the school system. The average wage is lower for workers confronted with overeducation. On the one hand, it can be due to the fact that they do not have a job corresponding to their level of qualification and are therefore paid less than if they did. On the other hand, the lower wage could explain the subjective feeling of being mismatched. If residential migration is not a predominant behaviour, it is not marginal either. Indeed, 38.4% of the workers have moved since graduation, among which about a quarter to Paris. When migrations are observed, they appear to be significant, with an average distance of around 350 km. However, French regions cover vast territories, and moving from one region to another often involves long distances. Despite this observation, it is worth noting that the average distance observed mainly reflects movements between neighbouring regions rather than between distant regions.

There are slightly more individuals who are statistically overeducated (27.5%) than those subjectively mismatched (25.1%). However, when we cross the two situations (Table 2), we observe that approximately 30% of the workers are mismatched in only one of the dimensions (around 13% are only subjectively mismatched, and more than 15% are only statistically overeducated). This confirms that these two situations do not systematically overlap, either due to the difference between overeducation and overskilling or because there is a distinction between the feeling of being overeducated and the fact of actually being mismatched. The situation is similar among individuals who have migrated, although the share of mismatched workers (in either one or both dimensions) is lower for this subpopulation. While it seems that there may be a relationship between migration and overeducation, an econometric analysis is necessary to establish whether or not there is a causal relationship.

³We use the definition of the regions at the time of the survey, i.e. to say, before a French territorial reform implemented in 2015. This definition corresponds to the NUTS 2 geographical divisions from Eurostat.

⁴According to the French National Institute of Statistics and Economic Studies (Insee), in 2013, 86.5% of workers had a permanent contract.

 TABLE 1
 Descriptive statistics.

							Statistica			
	Whole	sample	Migran	t	Employe	d	overedu	cation	Subjective	mismatch ———
	Mean	σ	Mean	σ	Mean	σ	Mean	σ	Mean	σ
Employed	81.7	0.003	83.4	0.004						
Migration	37.5	0.003			38.3	0.004	34.3	0.7	36.1	0.008
Migration distance (in km)			353.2	2.433	352.1	2.678	335.2	5.17	349.3	5.364
Migration to Paris	8.9	0.002	23.8	0.005	9.5	0.003	7.1	0.004	9.4	0.005
Statistically overeducated			20.5	0.005	27.5	0.004			48.3	0.009
Subjectively mismatched			19.7	0.005	25.1	0.004	44	0.008		
Demographic cha	racteristics	5								
Woman	55.9	0.003	53.8	0.006	56.1	0.004	53.4	0.008	51.5	0.008
Age	24.3	0.024	24.4	0.036	24.3	0.025	23.5	0.044	24.3	0.053
Children	13.4	0.002	11.6	0.004	13.1	0.003	9.3	0.004	13.5	0.006
Residential status										
Living alone	33.8	0.003	41.8	0.006	34.2	0.004	32.6	0.008	32.3	0.008
Living with a partner	49.2	0.004	49.1	0.006	51.5	0.004	43.5	0.008	48.4	0.008
Living with their parents	16.9	0.003	9	0.004	14.2	0.003	23.9	0.007	19.2	0.007
Educational level										
Two-year degree	36.2	0.004	27.6	0.006	37.8	0.004	25.2	0.007	28.8	0.007
Three- or four- year degree	22.3	0.003	21	0.005	20.4	0.003	39.6	0.008	28.5	0.007
Five-year degree or more	41.5	0.003	51.3	0.006	41.7	0.004	35.1	0.008	42.7	0.008
Field of study										
Education	0.4	0.001	0.3	0.001	0.4	0.001	0.3	0.001	0.004	0.001
Humanities	12.2	0.002	10.5	0.004	10.6	0.003	14.1	0.006	15.6	0.006
Economics, business and law	16.6	0.003	14	0.005	16	0.003	25.5	0.007	20.6	0.007
Science	15.9	0.002	19.7	0.005	16	0.003	11.9	0.005	15.8	0.006
Industry	15	0.003	17.6	0.005	15.7	0.003	20	0.007	17.2	0.006
Agriculture	2.4	0.001	3	0.002	2.2	0.001	4.5	0.003	2.5	0.003
Health	22.3	0.003	20	0.005	24.6	0.003	3.4	0.003	9.9	0.005
Services	14.9	0.003	14.7	0.005	14.2	0.003	19.8	0.007	17.7	0.007
Business sector Public sector					33.9	0.004	17	0.006	28.1	0.007



TABLE 1 (Continued)

	Whole :	sample	Migran	t	Employe	d	Statistica overeduc	- -	Subjective	e mismatch
	Mean	σ	Mean	σ	Mean	σ	Mean	σ	Mean	σ
Agriculture					0.7	0.001	1.9	0.002	0.6	0.001
Sales					9.9	0.003	21.2	0.007	17.1	0.007
Construction					2.4	0.001	2.4	0.003	2.2	0.003
Industry					9.5	0.003	13.6	0.006	11.7	0.006
Services					43.4	0.004	42.7	0.008	40.1	800.0
Job characteristics										
Wage					1835.8	6.034	1546.5	9.631	1641.5	10,958
Working full time					86.3	0.003	83.4	0.006	84.3	0.006
Permanent job					69.5	0.004	65.8	0.007	67.9	800.0
Time to get first job (in months)					2.3	0.040	3.2	0.091	3.1	0.093
Observations	15,865		5961		12,968		3570		3254	

Note: The migration distance provides the kilometres between the centroids of the departure and arrival regions. It is equal to 0 if there is no migration. The average is calculated only for people who have migrated in each subsample. The average wage is monthly.

Source: Authors' calculation based on Génération 2010 data.

TABLE 2 Correspondence between statistical overeducation and subjective mismatch.

		Subjective mismate	ch
		Matched	Overeducated
Employed (N = 12,968)			
Statistical Overeducation	Matched	7715	1683
		59.5%	13%
	Overeducated	1999	1571
		15.4%	12.1%
Migrant (N = 5961)			
Statistical Overeducation	Matched	4080	656
		68.4%	11%
	Overeducated	706	1571
		11.8%	8.7%

Source: Author's calculation based on Génération 2010 data.

5 | ESTIMATION STRATEGY

This work examines the links between migration (or spatial mobility) and overeducation for French young workers. However, the existence of a causal effect must be assessed in a regression framework controlling for possible sample selection bias and endogeneity of migration decisions.



Firstly, the estimated results may suffer from a sample selection problem because educational mismatch is observable only for graduates who are actually employed. Analysing the risk of overeducation while restricting the sample to young workers could lead to biased results. This bias may occur if the probability of being mismatched differs between individuals who decide to work and those who decide not to. For instance, some young people may choose inactivity or unemployment to avoid mismatch, and, thus, those least likely to accept a job could be the most likely to be overeducated. On the contrary, some young people may prefer to be mismatched rather than be unemployed. In this case, the aversion to the risk of unemployment is likely to increase the likelihood of accepting a mismatched job. Whatever the strategy retained, it indicates that some unobserved characteristics influencing the probability of being employed could also be related to the risk of mismatch.

We deal with this selection bias by using the standard two-step Heckman correction procedure (Heckman, 1979). Technically, the first step involves specifying an employment selection equation, which uses a probit model to explain the probability of being employed based on individuals' socio-economic characteristics. The equation is written as follows:

$$E = \beta_0 + \beta_1 X + \beta_2 Z + \epsilon \tag{1}$$

where

$$E = \begin{cases} 1 \text{ if } E^* > 0 \\ 0 \text{ otherwise} \end{cases}$$

In Equation 1, *E* represents the employment status (being employed or not), and *X* is a vector of various socioeconomic characteristics that are likely to influence the probability of employment for young people. We consider age, gender and family status of the young people, along with variables for their educational level and field of study. In addition, we include dummies for regions of residence to account for any unobserved heterogeneity between territories and local labour markets. Identifying the risk of overeducation with the presence of a sample selection bias requires at least one selection variable (*Z*) that is correlated with access to employment but unrelated to this risk. Finding such variables, also known as exclusion restrictions, can be challenging when working with observational data.

We retain health status as an exclusion restriction for the employment equation. In particular, we know if an individual is affected by a long-term health problem or disability. In fact, 7.4% of our sample is concerned, although we cannot identify whether it is a disability or not. We assume that experiencing a long-lasting health problem is likely to affect the likelihood of finding a job but should not have a direct influence on overeducation once we control for demographic characteristics, job-specific features and local variables. A large part of the literature in health economics has explored and demonstrated the links between health status and employment (see Vornholt et al., 2018 or Barnay, 2020, for recent reviews). For instance, several studies have shown that individuals with disabilities are often underemployed in the workforce. Regarding mental health as a health status, the relationship may be bidirectional (Banerjee et al., 2017). In other words, health status can influence employment positions, and, conversely, being employed (or not) can impact health status. However, having a disability restricts the bidirectional causal effect, as it can be attributed to accidents, genetic conditions or even congenital malformations (rather than employment status). In addition, because individuals in our sample declare being affected by a long-term health problem, we can reasonably assume that this health status precedes the time of the survey. This ensures that health status indeed determines the probability of employment. On the contrary, to the best of our knowledge, there is no empirical evidence of a direct link between health status and overeducation. While being mismatched could potentially lead to deterioration in mental health, using only long-term affections should mitigate the relevance of the

 $^{^5\}mbox{That}$ is, the French administrative regions. See Appendix B for more details.

phenomenon. In addition, more than 80% of the respondents suffering from a health condition report that it preceded their entry into the labour market.

Once we have taken into account the sample selection problem, we may consider the effect of migration on the risk of overeducation by estimating the following linear probability model⁶:

$$O = \beta_0 + \beta_1 X + \beta_2 Mobility + u$$
 (2)

where

$$O = \begin{cases} 1 \text{ if } O^* > 0 \\ 0 \text{ otherwise} \end{cases}$$

In Equation 2, *O* represents the variable of being overeducated or not. It is important to note that overeducation is measured in two ways, using statistical and subjective measures. In both cases, the vector of observable characteristics *X* does not vary and includes the same set of variables as defined for Equation 1, and some job-related characteristics such as the time needed to find the first job, the type of contract (permanent or not, full-time or not) and the activity sector (public, agricultural, industrial, construction, services, etc.). In addition, we consider two types of spatial mobility. In one case, mobility corresponds to migration from one region to another between graduation and the current job occupied. In the other case, it corresponds to migration to Paris exclusively.

A further econometric issue could arise from the endogeneity of the migration choice. It is likely that there is a potential correlation between overeducation and some unobserved factors that influence the decision to migrate or relocate to get a job. For example, risk-averse individuals might accept jobs that do not perfectly match their skills to avoid the costs and risks associated with migration. This implies that, in Equation 2, the spatial mobility decision is likely to be linked to unobservable individual characteristics that are correlated with the error term, resulting in biased estimates. To address this problem, we retain the instrumental variables method.

Previous studies addressing this endogeneity problem have used the lagged unemployment rate in the area from which the individual moved (Croce & Ghignoni, 2015). However, this approach has been criticized due to the questionable assumption that the lagged unemployment rate in a particular area has no influence on current overeducation in the same area, given the high persistence of local unemployment. As an alternative, some authors have used housing tenure as an instrument (Devillanova, 2013; Meliciani & Radicchia, 2016). The argument is that housing tenure should be correlated with migration because renters can move more easily than homeowners, but it is not directly correlated with the degree of overeducation. Because we lack information on housing tenure status, we follow the approach used by Venhorst and Cörvers (2018) and employ information on past mobility as instrumental variables (Z).

Firstly, we define a dummy variable that takes the value 1 if young people have migrated between the time they obtained their baccalaureate and their last degree (i.e. if they changed their region of residence during or for university studies) and 0 otherwise. This instrument, by capturing information on spatial mobility during education, is likely to explain recent mobility (DaVanzo & Morrison, 1981) without being directly connected to the actual risk of overeducation. However, one can argue that it is not totally convincing as past mobility might be correlated to unobserved characteristics (u) determining simultaneously recent mobility and risk of overeducation. It might be a certain ability and/or motivation of some individuals to succeed in their professional careers. For this reason, we retain a second instrumental variable providing information on whether or not young people have spent time abroad during their academic careers. We consider only mandatory stays abroad because they do not result from a direct voluntary choice of individuals concerned and are less likely to be correlated with omitted variables mentioned

⁶Some issues can arise from the use of linear probability models. Especially, they can predict probabilities outside the [0;1] interval. Figures C1 and C2 in Appendix C shows the distribution of predicted overeducation in our sample. In the case of our statistical measure of overeducation, only a small number of predicted probabilities are lower than 0, and none of them are higher than 1. In the case of our subjective measure, predicted probabilities are almost all between 0 and 1. Still, to check the robustness of our results, we estimate a triprobit model, which provides results similar to those obtained with linear probability models (see Section 6).

earlier. We then have: Cov(Z, u) = 0 and $Cov(Z, Mobility) \neq 0$. Our variable thus satisfies the two conditions of a good instrument (Wooldridge, 2002).

Equation 2 is estimated using the two-stage least squares (2SLS) procedure. We employ a linear probability model to explain the migration decision, incorporating the same set of variables as before, and our instrumental variables. Table D1 in Appendix D also presents the results for the first stage of the 2SLS, confirming that past migration and mandatory stays abroad are significantly and positively associated with recent migrations. In addition, we implement the weak instrument test of Olea and Pflueger (2013) to ensure the validity of our instruments. Our F-test values, which exceed the critical value reported by Stock and Yogo (2005), indicate that we have strong instruments.

Finally, we estimate the probability of being overeducated using three different econometric strategies. Firstly, it is estimated without any control for the selection into employment or the endogeneity of migration decision. Secondly, we control only for the selection bias. Thirdly, we control for both biases. In addition, we first estimate baseline models where individuals' educational level is distinguished through dummy variables to check whether they face a different risk of overeducation. Then, we proceed by performing separate estimations depending on the educational level of the graduates.

6 **RESULTS**

6.1 Effects of migration on overeducation

The results of our models are presented in Tables 3 (statistical overeducation) and 4 (subjective mismatch). The first column shows the baseline model without any correction for selection and endogeneity biases. The second and third columns present the results with correction for selection bias (column 2) and both selection and endogeneity biases (column 3). We will focus our discussion on the last column as it represents the most complete and robust model. On the whole, we find different effects for several variables depending on the type of mismatch we consider.

Firstly, the coefficients and significance for the inverse Mills ratio demonstrate the necessity to take into account the selection into employment in our analysis of the determinants of overeducation. In line with Devillanova (2013), they confirm the intuition that the probability of being overeducated is positively correlated with the probability of being unemployed. Overall, Tables 3 and 4 also reveal that self-selection has no influence on the coefficients of interest.

Concerning individual characteristics, we find that women are statistically more likely to be overeducated than men. This could be related to some difficulties in finding a 'good' job or potential discrimination experienced during the job search process. Consequently, when women are hired, they might be assigned to less-skilled positions. However, there is no significant gender difference for subjective mismatch, indicating that men and women have similar perceptions of the mismatch between their skills and job requirements. The age at the time of graduation has a negative effect on statistical overeducation but a small positive effect on subjective mismatch. In one case, this can be attributed to the fact that with age, individuals gain experience and skills that align better with job requirements, reducing the risk of overeducation. In the other case, the positive effect on subjective mismatch may suggest that older individuals are more critical of their jobs. Having children has no robust effect on overeducation, whatever the measure retained. However, being a woman with children reveals some negative effects depending on the estimation strategy retained. Although counterintuitive, this finding is in accordance with those obtained by Jauhiainen (2011). Regarding living with parents, we find a positive effect on statistical overeducation, although not always significant. Following Chevalier (2003), a significant effect might reflect lower abilities or lower motivation that affects both the decision to live with parents and the labour market positions. Surprisingly, we do not observe any significant effect for young people living with a partner on statistical overeducation but a positive and significant one on subjective mismatch. In this case, it could be due to the fact that individuals accept less favourable employment conditions when it comes to following their spouse.



 TABLE 3
 Linear probability models for statistical overeducation

TABLE 3 Linear probability models for	r statistical overeducat	ion.	
	OLS	Heckman	Heckman + IV
Constant	0.730***	0.669***	0.711***
	0.043	0.055	0.125
Migration	-0.038***	-0.038***	-0.072***
	0.009	0.009	0.017
Demographic characteristics			
Woman	0.062***	0.062***	0.062***
	0.007	0.007	0.008
Age	-0.016***	-0.016***	-0.017***
	0.002	0.002	0.002
Children	0.029	0.033	0.031*
	0.021	0.021	0.018
$Woman \times children$	-0.019	-0.055**	-0.055*
	0.025	0.022	0.031
Residential status (reference: living alone)			
Living with a partner	-0.001	0.012	0.010
	0.007	0.011	0.011
Living with their parents	0.108***	0.059*	0.052
	0.013	0.031	0.033
Educational level (reference: 2-year degre	e)		
Three- or four-year degree	0.248***	0.228***	0.233***
	0.020	0.023	0.018
Five-year degree or more	0.063***	0.054***	0.063***
	0.018	0.016	0.013
Field of study (reference: services)			
Education	-0.099	-0.057	-0.056
	0.068	0.064	0.059
Humanities	-0.013	-0.032	-0.034*
	0.024	0.028	0.019
Economics, business and law	0.058***	0.060***	0.059***
	0.014	0.014	0.013
Science	-0.091****	-0.081***	-0.080***
	0.018	0.016	0.014
Industry	-0.024	0.002	0.004
	0.016	0.016	0.020
Agriculture	0.106***	0.094***	0.098***
	0.030	0.032	0.027
Health	-0.215***	-0.182***	-0.180***
	0.020	0.020	0.025
Business sector (reference: services)			
Public sector	-0.078***	-0.078***	-0.077***
	0.010	0.010	0.008

TABLE 3 (Continued)

	OLS	Heckman	Heckman + IV
Agriculture	0.312***	0.311***	0.312***
	0.052	0.052	0.042
Sales	0.220***	0.221***	0.220***
	0.012	0.013	0.012
Construction	0.066*	0.067*	0.066***
	0.038	0.038	0.023
Industry	0.074***	0.075***	0.075***
	0.019	0.019	0.013
Job characteristics			
Working full time	-0.050***	-0.050***	-0.049***
	0.012	0.012	0.011
Permanent job	-0.050***	-0.049***	-0.050***
	0.009	0.009	0.008
Time to get first job	0.007***	0.006***	0.006***
	0.001	0.001	0.001
Inverse Mills ratio		0.232*	0.230*
		0.121	0.140
Region fixed effects	Yes	Yes	Yes
R-squared	0.251	0.251	0.250
N	12,968	12,962	12,962

Note: Standard errors are clustered by region. OLS = ordinary least squares.

Source: Authors' calculations based on Génération 2010 data.

We observe that the educational level has a strong effect on statistical overeducation but not necessarily on subjective mismatch. Compared to young people with a 2-year degree, those with more years of education are more likely to be overeducated. This is quite normal as it is less common to have a job below his education level if the latter is not very high. However, the risk of overeducation is highest for 3- or 4-year degree graduates. This might be due to the fact that these degrees represent transitional levels designed to give access to further studies. There is limited demand for these educational levels in the French labour market. This is especially true for 4-year degrees, which may not be sufficient for jobs requiring a master's degree, making them more susceptible to being preferred for positions that require a lower level of education, such as those asking for a bachelor's degree. Moreover, we find a negative effect of graduating in health-related fields on both dimensions of mismatch. While the field of study does not seem to affect subjective mismatch, our results show that graduates in economics, business and law and agriculture face a higher risk of statistical overeducation, whereas graduates in science are significantly less likely to be overeducated.

When we examine the job characteristics, we observe that the public sector seems to be the only one protected from overeducation. This could be attributed to the fact that most public service positions are allocated through formal entrance examinations, which reduces the likelihood of being hired for a job that does not match one's education. However, individuals in the public sector do not feel subjectively less mismatched. On the contrary, the

^{***}indicates significance at the 1% level.

^{**}at the 5% level.

^{*}at the 10% level.



TABLE 4 Linear probability models for subjective mismatch.

Constant 0.175*** 0.053 0.092 0.058 0.067 0.136 Migration −0.015 −0.015 −0.046 Demographic characteristics −0.010 0.010 0.019 Demographic characteristics −0.008 0.008 0.009 Age 0.008 0.008 0.009 Age 0.001 0.001 0.002 Children 0.024 0.028 0.027 Ou17 0.018 0.019 Woman × children 0.017 0.018 0.019 Woman × children 0.001 0.003** 0.0027 Woman × children 0.001 0.003** 0.003** Woman × children 0.002 0.03** 0.03** Woman × chi	Constant 0.175*** 0.053 0.092 Migration −0.015 −0.015 −0.046** Demographic characteristics −0.010 0.010 0.011 Woman 0.010 0.001 0.001 Age 0.005*** 0.004*** 0.003** Age 0.001 0.001 0.001 0.002* Children 0.024 0.028 0.027 0.073** Woman × children 0.001 0.018 0.019 Woman × children 0.001 0.008 0.018 0.019 Woman × children 0.001 0.008 0.018 0.019 Woman × children 0.001 0.003** 0.033** 0.033** Residential status (reference: living alone) Living with a partner 0.009 0.034*** 0.032*** Living with a partner 0.009 0.034**** 0.032*** 0.032*** Living with their parents 0.070*** -0.027 -0.033 0.035** Educational level (reference: 2-year degree) 0.036** <th>TABLE 4 Linear probability models fo</th> <th>r subjective mismatch.</th> <th></th> <th></th>	TABLE 4 Linear probability models fo	r subjective mismatch.		
Migration	Migration 0.058 0.067 0.136 Demographic characteristics −0.015 −0.015 −0.016 Woman 0.010 0.011 0.011 Age 0.005*** 0.004** 0.003** Age 0.001 0.001 0.001 Children 0.024 0.028 0.027 Children 0.001 0.018 0.019 Woman × children −0.001 −0.073** −0.073** Nound × children −0.001 −0.073** −0.073** Residential status (reference: living alone) Living with a partner 0.009 0.034*** 0.032*** Living with a partner 0.009 0.034*** 0.032*** 0.032*** Educational level (reference: 2-year degree) 0.008 0.012 0.012 Educational level (reference: 2-year degree) 0.036*** −0.005 −0.003 Educational level (reference: 2-year degree) 0.036*** −0.005 −0.000 Five-year degree or more 0.023 −0.040*** −0.032** <t< th=""><th></th><th>OLS</th><th>Heckman</th><th>Heckman + IV</th></t<>		OLS	Heckman	Heckman + IV
Migration −0.015 0.010 −0.015 0.010 −0.046** Demographic characteristics Woman 0.010 0.011 0.011 Woman 0.008 0.008 0.009 Age 0.005*** 0.004** 0.003** Children 0.024 0.028 0.027 Children 0.017 0.018 0.019 Woman × children −0.001 −0.073** −0.073** Nous × children 0.009 0.034*** 0.033 Residential status (reference: living alone) Living with a partner 0.009 0.034*** 0.033** Living with their parents 0.070*** −0.027 −0.033 0.032** Educational level (reference: 2-year degree) 0.036*** −0.0027 −0.033 Educational level (reference: 2-year degree) 0.036** −0.005 −0.000 Five-year degree or more 0.036** −0.005 −0.000 Five-year degree or more 0.023 −0.040*** −0.032** Education −0.066 0.017 0.018	Migration −0.015 −0.015 −0.016 −0.046** Demographic characteristics V Woman 0.010 0.011 0.011 0.011 0.001 Age 0.005*** 0.004** 0.003** −0.01 0.001 0.001 0.002 0.002** 0.002** Children 0.024 0.028 0.027** −0.017 0.018 0.019** 0.019** Woman × children −0.001 −0.073** −0.073** −0.023 0.037 0.033 0.034*** Residential status (reference: living alone) Living with a partner 0.009 0.034**** 0.032*** Living with their parents 0.070*** −0.027 −0.033 0.032*** 0.012 Living with their parents 0.070*** −0.027 −0.033 0.035** 0.034*** Fiducational level (reference: 2-year degree) 0.036*** −0.005 −0.000 −0.000 0.012 Educational level (reference: 2-year degree) 0.036*** −0.005 −0.000 −0.000 0.014 0.016 0.019 0.014 0.016 0.019 0.014 0.016 0.019 0.014 0.016 0.019 0.014 0.016 0.019 0.016 0.018 0.014 0.016 0.019 0.016	Constant	0.175***	0.053	0.092
Demographic characteristics	Demographic characteristics		0.058	0.067	0.136
Demographic characteristics Woman 0.010 0.011 0.011 Age 0.005" 0.004" 0.003" Age 0.001 0.001 0.002 Children 0.024 0.028 0.027 Uniforen 0.017 0.018 0.019 Woman × children -0.001 -0.073" -0.073" No.023 0.037 0.033 Residential status (reference: living alone) Living with a partner 0.009 0.034" 0.032" Living with a partner 0.009 0.034" 0.032" Living with their parents 0.0070" -0.027 -0.033 0.012 0.012 0.012 0.012 Living with their parents 0.070" -0.027 -0.033 0.019 0.038 0.012 0.012 Living with their parents 0.0070" -0.027 -0.033 0.019 0.038 0.012 0.012 Living with their parents 0.036 0.014 0.016 0	Demographic characteristics Woman 0.010 0.011 0.011 Age 0.005"** 0.004** 0.003** Age 0.001 0.001 0.002 Children 0.024 0.028 0.027 Uniforen 0.001 -0.073** -0.073** Woman × children -0.001 -0.073** -0.073** Nous Name 0.0023 0.037 0.033 Residential status (reference: living alone) Living with a partner 0.009 0.034*** 0.032*** 0.008 0.012 0.012 0.012 Living with their parents 0.070*** -0.027 -0.033 0.019 0.038 0.035* 0.035* Educational level (reference: 2-year degree) 0.036*** -0.005 -0.000 Educational level (reference: 2-year degree) 0.014 0.016 0.019 Five-year degree or more -0.023 -0.040*** -0.024 Education level (reference: services)	Migration	-0.015	-0.015	-0.046**
Woman 0.010 0.011 0.011 Age 0.005" 0.004" 0.003" Age 0.001 0.001 0.002 Children 0.024 0.028 0.027 0.017 0.018 0.019 Woman × children -0.001 -0.073" -0.073" Woman × children 0.0023 0.037 0.033 Residential status (reference: living alone) Using with a partner 0.009 0.034" 0.032" Living with a partner 0.009 0.034" 0.032" 1 0.009 0.034" 0.032" 0.012 Living with their parents 0.070" -0.027 -0.033 2 0.019 0.038 0.035 0.035 Educational level (reference: 2-year degree) 0.014 0.016 0.019 Five-year degree or more 0.023 -0.040" -0.022 1 0.014 0.016 0.019 0.014 Five-year degree or more 0.023 -0.040" -0.022 Education -	Woman 0.010 0.011 0.011 Age 0.005" 0.004" 0.003" Age 0.001 0.001 0.002 Children 0.024 0.028 0.027 0.017 0.018 0.019 Woman × children −0.001 −0.073" −0.073" Residential status (reference: living alone) Using with a partner 0.009 0.034" 0.032" Living with a partner 0.009 0.034" 0.032" 1008 0.012 0.012 0.012 Living with their parents 0.070" −0.027 −0.033 0.019 0.038 0.035 0.035 Educational level (reference: 2-year degree) 0.014 0.016 0.001 Three- or four-year degree 0.036" −0.005 −0.000 Five-year degree or more −0.023 −0.040" −0.022 6 tudy (reference: services) Education −0.066 0.017 0.018 Field of study (reference: services) 0.047 0.009 0.007<		0.010	0.010	0.019
Age 0.008 0.009* 0.003* Children 0.001 0.001 0.002 Children 0.024 0.028 0.027 Woman × children 0.0017 0.018 0.019 Woman × children 0.0021 0.003* 0.003* Residential status (reference: living alone) U 0.003* 0.032** Living with a partner 0.009 0.034*** 0.032** 1 0.008 0.012 0.012 0.012 Living with their parents 0.070** -0.027 -0.033 Educational level (reference: 2-year degree) 0.019* 0.038 0.035 Educational level (reference: 2-year degree) 0.036** -0.005 -0.000 Five-year degree or more -0.023 -0.040** -0.002 Five-year degree or more -0.023 -0.040** -0.032** Education -0.066 0.017 0.018 Humanities 0.047** 0.009 0.007 0.024 0.031 0.014 Economi	Age 0.008 0.008 0.009 Age 0.005" 0.004" 0.003" Children 0.001 0.001 0.002 Children 0.001 0.001 0.002 Children 0.001 0.001 0.002 Children 0.001 0.001 0.008 0.027 Woman × children 0.001 0.003 0.037 0.033 Residential status (reference: living alone) Living with a partner 0.009 0.034" 0.032" 1.008 0.012 0.012 Living with their parents 0.070" 0.038 0.035 Educational level (reference: 2-year degree) Three- or four-year degree 0.036" 0.005 0.009 Educational level (reference: 2-year degree) Three- or four-year degree 0.036" 0.005 0.009 Five-year degree or more 0.023 0.040" 0.032" Education 0.014 0.016 0.019 Five-year degree or more 0.003 0.014 Five-year degree or more 0.003 0.014 Education 0.009 0.007 Five-year degree or more 0.006 0.017 0.018 0.009 0.007 Education 0.009 0.007 Education 0.009 0.007 Five-year degree or more 0.006 0.017 0.018 0.009 0.009 0.007 Education 0.009 0.007 Five-year degree or more 0.006 0.017 0.018 0.009 0.009 0.007 Education 0.009 0.007 Five-year degree or more 0.0009 0.007 Education 0.009 0.007 Five-year degree or more 0.009 0.007 Education 0.009 0.009 Education 0.009 Education 0.009 Educational level (reference: 2-year degree) Educational level (reference: 2-year d	Demographic characteristics			
Age 0.005*** 0.004** 0.003** Children 0.024 0.028 0.027 Woman × children 0.001 -0.073** -0.073** Woman × children -0.001 -0.073** -0.073** n.023 0.037 0.033 Residential status (reference: living alone) Living with a partner 0.009 0.034*** 0.032*** 1 0.008 0.012 0.012 0.012 Living with their parents 0.008 0.012 0.012 Living with their parents 0.009** -0.027** -0.033 Educational level (reference: 2-year degree) Three- or four-year degree 0.036** -0.005** -0.000 0.014 0.016 0.019** -0.000 Five-year degree or more -0.023 -0.040*** -0.032** Education -0.024 0.014 0.014 Field of study (reference: services) -0.040*** 0.009 0.007 -0.025 0.024 0.001 0.014	Age 0.005*** 0.004** 0.003** Children 0.024 0.028 0.027 Woman × children 0.001 -0.073** -0.073** Noman × children 0.0021 -0.073** -0.073** Noman × children 0.0023 0.003 0.033 Residential status (reference: living alone) V V V Living with a partner 0.009 0.034*** 0.032*** 1 0.008 0.012 0.012 0.012 Living with their parents 0.008 0.012 0.012 Living with their parents 0.008 0.012 0.012 Living with their parents 0.009** 0.038 0.035** Educational level (reference: 2-year degree) 0.019** 0.002** 0.003** Educational level (reference: 2-year degree) 0.036** 0.005** 0.000** Five-year degree or more 0.023 0.040** 0.014** Five-year degree or more 0.023 0.040** 0.03** Field of study (reference: services) <t< td=""><td>Woman</td><td>0.010</td><td>0.011</td><td>0.011</td></t<>	Woman	0.010	0.011	0.011
Children 0.001 0.002 Children 0.024 0.028 0.027 Voman × children −0.001 −0.073* −0.073* Residential status (reference: living alone) Voman × children −0.003 0.034** −0.023* Residential status (reference: living alone) Universidential status (reference: living alone) Voman × children 0.009* 0.034*** 0.032*** Living with a partner 0.009* 0.034*** 0.032*** 0.0012 0.012 Living with their parents 0.0070*** −0.027 −0.033 0.035 0.0012 Living with a partner 0.009* 0.038 0.035 0.003 0.035 0.0012 0.012 0.012 0.012 0.012 0.012 0.012 0.003 0.035 0.005 −0.003 0.035 0.005 −0.000 0.0019 0.0019 0.0019 0.0019 0.0019 0.0019 0.0019 0.0019 0.0019 0.0019 0.0019 0.0019 0.0019 0.0019 0.0018 0.0014 0.014	Children 0.001 0.002 Children 0.024 0.028 0.027 Voman × children −0.001 −0.073* −0.073* Pesidential status (reference: living alone) Voman × children −0.003 0.037 0.033 Residential status (reference: living alone) Voman × children 0.009 0.034*** 0.032*** Living with a partner 0.009 0.034*** 0.032*** −0.002 0.008 0.012 0.012 0.012 Living with their parents 0.0070*** −0.027 −0.033 0.019 0.038 0.035 −0.000 Educational level (reference: 2-year degree) 0.036*** −0.005 −0.000 Five-year degree or more 0.036*** −0.005 −0.000 Five-year degree or more 0.023 −0.040*** −0.002 Education −0.026 0.017 0.018 Education −0.066 0.017 0.018 Humanities 0.047** 0.009 0.007 0.014		0.008	0.008	0.009
Children 0.024 0.018 0.019 Woman × children −0.001 −0.073* −0.073* Residential status (reference: living alone) Using with a partner 0.009 0.034*** 0.032*** Living with a partner 0.009 0.034*** 0.032*** Living with their parents 0.0070*** −0.027 −0.033 Living with their parents 0.019 0.038 0.035* Educational level (reference: 2-year degree) Three- or four-year degree 0.036** −0.005 −0.000 Five-year degree or more −0.023 −0.040** −0.032** Field of study (reference: services) Education −0.066 0.017 0.018 Education −0.066 0.017 0.018 0.004 Humanities 0.047* 0.009 0.007 0.024 0.031 0.014 Economics, business and law 0.004 0.008 0.007 0.015 0.015 0.015 0.015 Industry −0.025 0.025 0.027 <td>Children 0.024 0.018 0.019 Woman × children −0.001 −0.073* −0.073* Residential status (reference: living alone) Living with a partner 0.009 0.034*** 0.032*** Living with their parents 0.009* 0.034*** 0.032*** Living with their parents 0.0070*** −0.027 −0.033 Living with their parents 0.019* 0.038 0.035* Educational level (reference: 2-year degree) 0.019* −0.005 −0.000 Three- or four-year degree 0.036** −0.005 −0.000 Five-year degree or more −0.023 −0.040** −0.032** Field of study (reference: services) Education −0.066 0.017 0.018 Education −0.066 0.017 0.018 0.004 Humanities 0.047* 0.009 0.007 0.024 0.031 0.014 Economics, business and law 0.004 0.008 0.007 0.015 0.015 0.015 0.015</td> <td>Age</td> <td>0.005***</td> <td>0.004**</td> <td>0.003**</td>	Children 0.024 0.018 0.019 Woman × children −0.001 −0.073* −0.073* Residential status (reference: living alone) Living with a partner 0.009 0.034*** 0.032*** Living with their parents 0.009* 0.034*** 0.032*** Living with their parents 0.0070*** −0.027 −0.033 Living with their parents 0.019* 0.038 0.035* Educational level (reference: 2-year degree) 0.019* −0.005 −0.000 Three- or four-year degree 0.036** −0.005 −0.000 Five-year degree or more −0.023 −0.040** −0.032** Field of study (reference: services) Education −0.066 0.017 0.018 Education −0.066 0.017 0.018 0.004 Humanities 0.047* 0.009 0.007 0.024 0.031 0.014 Economics, business and law 0.004 0.008 0.007 0.015 0.015 0.015 0.015	Age	0.005***	0.004**	0.003**
Moman × children —0.001	Woman × children 0.017 0.018 0.019 Woman × children −0.001 −0.073* −0.073* Residential status (reference: living alone) Use a contract of the partner 0.009 0.034*** 0.032*** Living with a partner 0.009 0.034*** 0.032*** 1 0.008 0.012 0.012 Living with their parents 0.070*** −0.027 −0.033 0.019 0.038 0.035 Educational level (reference: 2-year degree) Use a contract of the partner −0.001 −0.005 −0.000 Five-year degree or more 0.036** −0.005 −0.000 Five-year degree or more −0.023 −0.040** −0.032** Education −0.023 −0.040** −0.032** Education −0.066 0.017 0.018 Humanities 0.047* 0.009 0.007 0.024 0.031 0.014 Economics, business and law 0.004 0.008 0.007 0.015 0.015 0.015		0.001	0.001	0.002
Woman × children −0.001 (0.023) −0.073* (0.033) Residential status (reference: living alone) Use of the partner (0.009) 0.034*** (0.032***) Living with a partner (0.008) 0.012 0.012 Living with their parents (0.070***) −0.027 −0.033 Living with their parents (0.019) 0.038 0.035 Educational level (reference: 2-year degree) 0.019 0.038 0.035 Educational level (reference: 2-year degree) 0.014 0.005 −0.000 Five-year degree or more (0.014) 0.016 0.019 Five-year degree or more (0.014) 0.013 0.014 Field of study (reference: services) Use of the partner of the pa	Woman × children −0.001 (0.023) −0.073* (0.033) Residential status (reference: living alone) Using with a partner 0.009 (0.034***) 0.032*** Living with their parents 0.009 (0.008) 0.012 (0.012) 0.012 Living with their parents 0.070*** −0.027 (0.033) −0.033 Educational level (reference: 2-year degree) 0.019 (0.036**) −0.005 (0.006) −0.000 Five-year degree or more 0.036** (0.014) −0.016 (0.019) −0.032** Five-year degree or more −0.023 (0.014) −0.013 (0.014) −0.014 Field of study (reference: services) Education −0.066 (0.017) 0.018 (0.004) Education −0.066 (0.017) 0.018 (0.004) 0.003 (0.004) Humanities 0.047* (0.009) 0.007 (0.004) 0.004 Economics, business and law 0.004* (0.008) 0.007 0.004 Science −0.039* (0.004) 0.008 0.007 Industry −0.025 (0.025) 0.025 0.027 Agriculture −0.032 (0.004) 0.004 0.005 Health	Children	0.024	0.028	0.027
Dodd	Dodd		0.017	0.018	0.019
Residential status (reference: living alone) Living with a partner 0.009 0.034*** 0.032*** 1	Residential status (reference: living alone) Living with a partner 0.009 0.034*** 0.032**** 0.008 0.012 0.019 0.038 0.035 0.035 0.035 0.005 0.000 0.014 0.016 0.019 0.014 0.016 0.019 0.014 0.016 0.019 0.014 0.016 0.019 0.014 0.013 0.014 0.014 0.013 0.014 0.014 0.015 0.015 0.015 0.015 0.006 0.017 0.018 0.039 0.040 0.063 0.007 0.018 0.007	$Woman \times children$	-0.001	-0.073*	-0.073**
Living with a partner 0.009 0.034*** 0.032*** Living with their parents 0.070*** −0.027 −0.033 Living with their parents 0.070*** −0.027 −0.033 Educational level (reference: 2-year degree) 0.019 0.038 0.035 Three- or four-year degree 0.036*** −0.005 −0.000 Five-year degree or more −0.023 −0.040*** −0.032** Five-year degree or more −0.023 −0.040*** −0.032** 0.014 0.013 0.014 Field of study (reference: services) Education −0.066 0.017 0.018 Humanities 0.047* 0.009 0.007 Humanities 0.047* 0.009 0.007 0.024 0.031 0.014 Economics, business and law 0.004 0.008 0.007 0.014 0.014 0.014 Science −0.039** −0.021 −0.020 0.015 0.015 0.015 Industry −0.025 <	Living with a partner 0.009 0.034*** 0.032*** Living with their parents 0.070*** −0.027 −0.033 Living with their parents 0.070*** −0.027 −0.033 Douly 0.038 0.035 Educational level (reference: 2-year degree) 0.036*** −0.005 −0.000 Three- or four-year degree 0.034** 0.016 0.019 Five-year degree or more −0.023 −0.040** −0.032** 0.014 0.013 0.014 Field of study (reference: services) 0.066 0.017 0.018 Education −0.066 0.017 0.018 Humanities 0.047** 0.009 0.007 Humanities 0.047* 0.009 0.007 Economics, business and law 0.004 0.008 0.007 Science −0.039** −0.021 −0.020 0.015 0.015 0.015 0.015 Industry −0.025 0.025 0.027 Agriculture −0.032		0.023	0.037	0.033
Living with their parents 0.008 0.012 0.012 Living with their parents 0.070*** −0.027 −0.033 0.019 Cducational level (reference: 2-year degree) Educational level (reference: 2-year degree) Three- or four-year degree 0.036** −0.005 −0.000 0.014 0.016 0.019 Five-year degree or more −0.023 −0.040*** −0.032** 0.014 0.013 0.014 Field of study (reference: services) Education −0.066 0.017 0.018 0.039 0.040 0.063 Humanities 0.047* 0.009 0.007 0.007 Living 0.024 0.031 0.014 Economics, business and law 0.004 0.008 0.007 0.014 0.014 0.014 0.014 Science −0.039** −0.021 −0.020 0.015 Industry −0.025 0.025 0.025 0.027 0.024 0.027 0.022 Agriculture −0.032 −0.054 −0.050* 0.029 Health −0.180** −0.0116*** −0.0116*** −0.0114*** 0.015 0.024 0.027 Business sector (reference: services) Fublic sector (reference: services)	Living with their parents 0.008 0.012 0.012 Living with their parents 0.070*** −0.027 −0.033 0.019	Residential status (reference: living alone)			
Living with their parents 0.070*** -0.027 -0.033 Educational level (reference: 2-year degree) -0.036** -0.005 -0.000 Three- or four-year degree 0.036** -0.005 -0.000 10.014 0.016 0.019 Five-year degree or more -0.023 -0.040*** -0.032** 10.014 0.013 0.014 Field of study (reference: services) -0.066 0.017 0.018 Education -0.066 0.017 0.018 10.039 0.040 0.063 Humanities 0.047* 0.009 0.007 10.024 0.031 0.014 Economics, business and law 0.004 0.008 0.007 10.014 0.014 0.014 0.014 Science -0.039** -0.021 -0.020 10.015 0.015 0.015 Industry -0.025 0.025 0.027 Agriculture -0.032 -0.054 -0.050* 0.033 0.033	Living with their parents 0.070*** -0.027 -0.033 Educational level (reference: 2-year degree) V Three- or four-year degree 0.036** -0.005 -0.000 10014 0.016 0.019 Five-year degree or more -0.023 -0.040*** -0.032** 10014 0.013 0.014 Field of study (reference: services) V V Education -0.066 0.017 0.018 10039 0.040 0.063 Humanities 0.047* 0.009 0.007 10024 0.031 0.014 Economics, business and law 0.004 0.008 0.007 10015 0.014 0.014 0.014 Science -0.039** -0.021 -0.020 1015 0.015 0.015 Industry -0.025 0.025 0.027 1024 0.027 0.022 Agriculture -0.032 -0.054 -0.050* 1033 0.033	Living with a partner	0.009	0.034***	0.032***
Educational level (reference: 2-year degree) 0.019 0.038 0.035 Three- or four-year degree 0.036** -0.005 -0.000 Five-year degree or more 0.014 0.016 0.019 Five-year degree or more -0.023 -0.040*** -0.032** 0.014 0.013 0.014 Field of study (reference: services) Education -0.066 0.017 0.018 10.039 0.040 0.063 Humanities 0.047* 0.009 0.007 10.024 0.031 0.014 10.014 0.014 0.014 10.015 0.015 0.015 10.015 0.015 0.015 10.024 0.027 0.022 Agriculture -0.032 -0.054 -0.050* 10.033 0.037 0.029 Health -0.180*** -0.116*** -0.114*** 10.015 0.024 0.027 10.025 0.024 0.027 10.02	Educational level (reference: 2-year degree) 0.019 0.038 0.035 Three- or four-year degree 0.036** -0.005 -0.000 Five-year degree or more 0.014 0.016 0.019 Five-year degree or more -0.023 -0.040*** -0.032** 0.014 0.013 0.014 Field of study (reference: services) Education -0.066 0.017 0.018 10.039 0.040 0.063 Humanities 0.047* 0.009 0.007 10.024 0.031 0.014 10.014 0.014 0.014 0.014 10.015 0.015 0.015 0.015 10.015 0.015 0.015 0.015 10.024 0.027 0.022 Agriculture -0.032 -0.054 -0.050* 10.031 0.016** -0.0116** -0.114*** 10.015 0.016** -0.0116** -0.114*** 10.024 0.024 0.027 0.024		0.008	0.012	0.012
Educational level (reference: 2-year degree) Three- or four-year degree 0.036** -0.005 -0.000 Five-year degree or more -0.023 -0.040*** -0.032** -0.014 0.013 0.014 Field of study (reference: services) Education -0.066 0.017 0.018 -0.039 0.040 0.063 Humanities 0.047* 0.009 0.007 -0.024 0.031 0.014 Economics, business and law 0.004 0.008 0.007 Science -0.039** -0.021 -0.020 0.015 0.015 0.015 Industry -0.025 0.025 0.027 Agriculture -0.032 -0.054 -0.050* Agriculture -0.032 -0.054 -0.050* Health -0.180*** -0.116*** -0.114*** -0.016** 0.015 0.024 0.027 Business sector (reference: services) -0.003 0.003 0.004 </td <td>Educational level (reference: 2-year degree) Three- or four-year degree 0.036** −0.005 −0.000 6.0014 0.016 0.019 Five-year degree or more −0.023 −0.040*** −0.032** 0.014 0.013 0.014 Field of study (reference: services) Education −0.066 0.017 0.018 0.039 0.040 0.063 Humanities 0.047* 0.009 0.007 0.024 0.031 0.014 Economics, business and law 0.004 0.008 0.007 6.0014 0.014 0.014 0.014 9.0024 0.014 0.014 0.014 9.0025 0.025 0.025 0.027 10.015 0.015 0.015 0.022 Agriculture −0.032 −0.054 −0.050* 10.033 0.033 0.037 0.029 Health −0.180*** −0.116*** −0.114*** 10.014 0.002 <td< td=""><td>Living with their parents</td><td>0.070***</td><td>-0.027</td><td>-0.033</td></td<></td>	Educational level (reference: 2-year degree) Three- or four-year degree 0.036** −0.005 −0.000 6.0014 0.016 0.019 Five-year degree or more −0.023 −0.040*** −0.032** 0.014 0.013 0.014 Field of study (reference: services) Education −0.066 0.017 0.018 0.039 0.040 0.063 Humanities 0.047* 0.009 0.007 0.024 0.031 0.014 Economics, business and law 0.004 0.008 0.007 6.0014 0.014 0.014 0.014 9.0024 0.014 0.014 0.014 9.0025 0.025 0.025 0.027 10.015 0.015 0.015 0.022 Agriculture −0.032 −0.054 −0.050* 10.033 0.033 0.037 0.029 Health −0.180*** −0.116*** −0.114*** 10.014 0.002 <td< td=""><td>Living with their parents</td><td>0.070***</td><td>-0.027</td><td>-0.033</td></td<>	Living with their parents	0.070***	-0.027	-0.033
Three- or four-year degree 0.036** −0.005 −0.000 Five-year degree or more −0.023 −0.040*** −0.032** Field of study (reference: services) −0.066 0.017 0.018 Education −0.066 0.017 0.018 Humanities 0.047* 0.009 0.007 0.024 0.031 0.014 Economics, business and law 0.004 0.008 0.007 0.014 0.014 0.014 Science −0.039** −0.021 −0.020 1ndustry −0.025 0.025 0.027 Agriculture −0.032 −0.054 −0.050* 0.033 0.037 0.029 Health −0.180*** −0.116*** −0.114*** 0.015 0.024 0.027	Three- or four-year degree 0.036** −0.005 −0.000 Five-year degree or more −0.023 −0.040*** −0.032** Field of study (reference: services) −0.066 0.017 0.018 Education −0.066 0.017 0.018 Humanities 0.047* 0.009 0.007 0.024 0.031 0.014 Economics, business and law 0.004 0.008 0.007 0.014 0.014 0.014 Science −0.039** −0.021 −0.020 10dustry −0.025 0.025 0.027 10dustry −0.025 0.025 0.027 Agriculture −0.032 −0.054 −0.050* 10dustry −0.180*** −0.116*** −0.114*** 10dustry −0.032 −0.054 −0.050* 10dustry −0.032 −0.054 −0.050* 10dustry −0.016*** −0.016*** −0.016*** 10dustry −0.050** −0.050** −0.050**		0.019	0.038	0.035
0.014	0.014 0.016 0.019	Educational level (reference: 2-year degree	ee)		
Five-year degree or more -0.023 -0.040*** -0.032** 0.014 0.013 0.014 Field of study (reference: services) Education -0.066 0.017 0.018 0.039 0.040 0.063 Humanities 0.047* 0.009 0.007 0.024 0.031 0.014 Economics, business and law 0.004 0.008 0.007 0.014 0.014 0.014 0.014 Science -0.039** -0.021 -0.020 0.015 0.015 0.015 0.015 Industry -0.025 0.025 0.027 0.022 Agriculture -0.032 -0.054 -0.050* 0.033 0.037 0.029 Health -0.180*** -0.116*** -0.114*** 0.015 0.024 0.027 0.024 Business sector (reference: services) 0.003 0.003 0.003 0.004	Five-year degree or more -0.023 -0.040*** -0.032** 0.014 0.013 0.014 Field of study (reference: services) Education -0.066 0.017 0.018 0.039 0.040 0.063 Humanities 0.047* 0.009 0.007 0.024 0.031 0.014 Economics, business and law 0.004 0.008 0.007 0.014 0.014 0.014 0.014 Science -0.039** -0.021 -0.020 0.015 0.015 0.015 0.015 Industry -0.025 0.025 0.027 0.022 Agriculture -0.032 -0.054 -0.050* 0.033 0.037 0.029 Health -0.180*** -0.116*** -0.114*** 0.015 0.024 0.027 0.022 Business sector (reference: services) 0.003 0.003 0.003 0.004	Three- or four-year degree	0.036**	-0.005	-0.000
Double	Double		0.014	0.016	0.019
Field of study (reference: services) Education -0.066 0.017 0.018 0.039 0.040 0.063 Humanities 0.047 0.009 0.007 0.024 0.031 0.014 Economics, business and law 0.004 0.008 0.007 0.014 0.014 0.014 0.014 Science -0.039** -0.021 -0.020 0.015 0.015 0.015 0.015 Industry -0.025 0.025 0.027 Agriculture -0.032 -0.054 -0.050* Agriculture -0.032 -0.054 -0.050* Health -0.180** -0.116** -0.114** 0.015 0.024 0.027 Business sector (reference: services) Public sector 0.003 0.003 0.003 0.004	Field of study (reference: services) Education -0.066 0.017 0.018 0.039 0.040 0.063 Humanities 0.047 0.009 0.007 0.024 0.031 0.014 Economics, business and law 0.004 0.008 0.007 0.014 0.014 0.014 0.014 Science -0.039** -0.021 -0.020 0.015 0.015 0.015 0.015 Industry -0.025 0.025 0.027 Agriculture -0.032 -0.054 -0.050* 0.033 0.037 0.029 Health -0.180** -0.116** -0.114** 0.015 0.024 0.027 Business sector (reference: services) 0.003 0.003 0.004	Five-year degree or more	-0.023	-0.040***	-0.032**
Education -0.066 0.017 0.018 Humanities 0.047* 0.009 0.007 0.024 0.031 0.014 Economics, business and law 0.004 0.008 0.007 0.014 0.014 0.014 0.014 Science -0.039** -0.021 -0.020 10dustry -0.025 0.025 0.027 10dustry 0.024 0.027 0.022 Agriculture -0.032 -0.054 -0.050* Health -0.180*** -0.116*** -0.114*** 0.015 0.024 0.027 0.029 Business sector (reference: services) Public sector 0.003 0.003 0.003 0.004	Education -0.066 0.017 0.018 Humanities 0.047* 0.009 0.007 0.024 0.031 0.014 Economics, business and law 0.004 0.008 0.007 0.014 0.014 0.014 0.014 Science -0.039** -0.021 -0.020 10dustry -0.025 0.025 0.027 10dustry -0.024 0.027 0.022 Agriculture -0.032 -0.054 -0.050* 10dustry -0.180*** -0.116*** -0.114*** 10dustry 0.003 0.024 0.027 Business sector (reference: services) 0.015 0.024 0.027		0.014	0.013	0.014
Humanities 0.039 0.040 0.063 Humanities 0.047° 0.009 0.007 0.024 0.031 0.014 Economics, business and law 0.004 0.008 0.007 0.014 0.014 0.014 0.014 Science -0.039°° -0.021 -0.020 10dustry -0.025 0.025 0.027 10dustry -0.025 0.025 0.027 Agriculture -0.032 -0.054 -0.050° 10dustry -0.033 0.037 0.029 Health -0.180°° -0.116°° -0.114°° 0.015 0.024 0.027 Business sector (reference: services) 0.003 0.003 0.004	Humanities 0.039 0.040 0.063 Humanities 0.047* 0.009 0.007 0.024 0.031 0.014 Economics, business and law 0.004 0.008 0.007 0.014 0.014 0.014 Science -0.039** -0.021 -0.020 0.015 0.015 0.015 Industry -0.025 0.025 0.027 0.024 0.027 0.022 Agriculture -0.032 -0.054 -0.050* 0.033 0.037 0.029 Health -0.180** -0.116** -0.114** 0.015 0.024 0.027 Business sector (reference: services) Public sector 0.003 0.003 0.003	Field of study (reference: services)			
Humanities 0.047* 0.009 0.007 0.024 0.031 0.014 Economics, business and law 0.004 0.008 0.007 0.014 0.014 0.014 0.014 Science -0.039** -0.021 -0.020 0.015 0.015 0.015 0.015 Industry -0.025 0.025 0.027 Agriculture -0.032 -0.054 -0.050* Agriculture -0.033 0.037 0.029 Health -0.180*** -0.116*** -0.114*** 0.015 0.024 0.027 Business sector (reference: services) Public sector 0.003 0.003 0.003 0.004	Humanities 0.047* 0.009 0.007 0.024 0.031 0.014 Economics, business and law 0.004 0.008 0.007 0.014 0.014 0.014 0.014 Science -0.039** -0.021 -0.020 0.015 0.015 0.015 Industry -0.025 0.025 0.027 Agriculture -0.032 -0.054 -0.050* Agriculture -0.032 -0.054 -0.050* Health -0.180*** -0.116*** -0.114*** 0.015 0.024 0.027 Business sector (reference: services) Public sector 0.003 0.003 0.003 0.004	Education	-0.066	0.017	0.018
Dodd	Double		0.039	0.040	0.063
Economics, business and law 0.004 0.008 0.007 0.014 0.014 0.014 0.014 Science -0.039** -0.021 -0.020 0.015 0.015 0.015 Industry -0.025 0.025 0.027 0.024 0.027 0.022 Agriculture -0.032 -0.054 -0.050* Health -0.180*** -0.116*** -0.114*** 0.015 0.024 0.027 Business sector (reference: services) Public sector 0.003 0.003 0.003 0.004	Economics, business and law 0.004 0.008 0.007 0.014 0.014 0.014 0.014 Science -0.039** -0.021 -0.020 0.015 0.015 0.015 Industry -0.025 0.025 0.027 0.024 0.027 0.022 Agriculture -0.032 -0.054 -0.050* Health -0.180*** -0.116*** -0.114*** 0.015 0.024 0.027 Business sector (reference: services) Public sector 0.003 0.003 0.004	Humanities	0.047*	0.009	0.007
Science 0.014 0.014 0.014 Industry -0.025 0.025 0.027 Agriculture -0.032 -0.054 -0.050* Health -0.180*** -0.116*** -0.114*** Business sector (reference: services) Public sector 0.003 0.003 0.003 0.004	Science 0.014 0.014 0.014 Industry -0.025 0.025 0.027 Agriculture -0.032 -0.054 -0.050* Health -0.180*** -0.116*** -0.114*** Business sector (reference: services) Public sector 0.003 0.003 0.003 0.004		0.024	0.031	0.014
Science -0.039** -0.021 -0.020 Industry -0.025 0.025 0.027 0.024 0.027 0.022 Agriculture -0.032 -0.054 -0.050* Health -0.180*** -0.116*** -0.114*** Dublic sector (reference: services) Public sector 0.003 0.003 0.003 0.004	Science -0.039** -0.021 -0.020 Industry -0.025 0.025 0.027 0.024 0.027 0.022 Agriculture -0.032 -0.054 -0.050* Health -0.180*** -0.116*** -0.114*** 0.015 0.024 0.027 Business sector (reference: services) Public sector 0.003 0.003 0.004	Economics, business and law	0.004	0.008	0.007
Double	Double		0.014	0.014	0.014
Industry -0.025 0.025 0.027 0.024 0.027 0.022 Agriculture -0.032 -0.054 -0.050* Health -0.180*** -0.116*** -0.114*** Business sector (reference: services) -0.003 0.003 0.003 0.004 Public sector 0.003 0.003 0.004 0.004	Industry -0.025 0.025 0.027 0.024 0.027 0.022 Agriculture -0.032 -0.054 -0.050* Health -0.180*** -0.116*** -0.114*** 0.015 0.024 0.027 Business sector (reference: services) Public sector 0.003 0.003 0.004	Science	-0.039**	-0.021	-0.020
Agriculture 0.024 0.027 0.022 Agriculture -0.032 -0.054 -0.050° 0.033 0.037 0.029 Health -0.180*** -0.116*** -0.114*** 0.015 0.024 0.027 Business sector (reference: services) Public sector 0.003 0.003 0.004	Agriculture 0.024 0.027 0.022 Agriculture -0.032 -0.054 -0.050° 0.033 0.037 0.029 Health -0.180*** -0.116*** -0.114*** 0.015 0.024 0.027 Business sector (reference: services) Public sector 0.003 0.003 0.004		0.015	0.015	0.015
Agriculture -0.032 -0.054 -0.050* 0.033 0.037 0.029 Health -0.180*** -0.116*** -0.114*** 0.015 0.024 0.027 Business sector (reference: services) Public sector 0.003 0.003 0.004	Agriculture -0.032 -0.054 -0.050* 0.033 0.037 0.029 Health -0.180*** -0.116*** -0.114*** 0.015 0.024 0.027 Business sector (reference: services) Public sector 0.003 0.003 0.004	Industry	-0.025	0.025	0.027
0.033 0.037 0.029 Health	Health 0.033 0.037 0.029 -0.180*** -0.116*** -0.114*** 0.015 0.024 0.027 Business sector (reference: services) Public sector 0.003 0.003 0.004		0.024	0.027	0.022
Health -0.180*** -0.116*** -0.114*** 0.015 0.024 0.027 Business sector (reference: services) Public sector 0.003 0.003 0.004	Health -0.180*** -0.116*** -0.114*** 0.015 0.024 0.027 Business sector (reference: services) Public sector 0.003 0.003 0.004	Agriculture	-0.032	-0.054	-0.050*
Business sector (reference: services) 0.015 0.024 0.027 Public sector 0.003 0.003 0.004	Business sector (reference: services) 0.003 0.003 0.004 Public sector 0.003 0.003 0.004		0.033	0.037	0.029
Business sector (reference: services) Public sector 0.003 0.003 0.004	Business sector (reference: services) Public sector 0.003 0.003 0.004	Health	-0.180***	-0.116***	-0.114***
Public sector 0.003 0.003 0.004	Public sector 0.003 0.003 0.004		0.015	0.024	0.027
		Business sector (reference: services)			
	0.009 0.009 0.009	Public sector	0.003	0.003	0.004
0.009 0.009 0.009			0.009	0.009	0.009

TABLE 4 (Continued)

	OLS	Heckman	Heckman + IV
Agriculture	-0.042	-0.044	-0.042
	0.041	0.041	0.045
Sales	0.159***	0.159***	0.158***
	0.013	0.014	0.013
Construction	-0.021	-0.019	-0.020
	0.035	0.035	0.025
Industry	0.059**	0.060**	0.060**
	0.024	0.024	0.014
Job characteristics			
Working full time	-0.046***	-0.046***	-0.045***
	0.013	0.013	0.012
Permanent job	-0.004	-0.003	-0.004
	0.012	0.012	0.009
Time to get first job	0.007***	0.007***	0.007***
	0.001	0.001	0.001
Inverse Mills ratio		0.456***	0.455***
		0.136	0.156
Region fixed effects	Yes	Yes	Yes
R-squared	0.074	0.074	0.073
N	12,968	12,962	12,962

Note: Standard errors are clustered by region. OLS = ordinary least squares.

Source: Authors' calculations based on Génération 2010 data.

agriculture and construction sectors have the highest risk of overeducation. These sectors often involve manual work, and such jobs typically do not require high levels of qualifications from workers.

The estimated coefficient for the variable 'working full time' indicates that this situation is associated with a lower risk of statistical overeducation. One possible explanation is that young workers are more selective when choosing a full-time job and are less likely to accept being overeducated for such positions. On the contrary, the negative sign associated with permanent contracts in Table 3 supports this view and is in line with the findings of Baert and Verhaest (2019), who argued that overeducation might be deemed acceptable only for temporary positions. We also observe that the time to get the first job is positively correlated with the risk of overeducation. Young people who have spent the most time searching for a job may decide to take a lower-quality job rather than continue to do so, especially to avoid the more detrimental effects of unemployment on future labour market positions (Baert & Verhaest, 2019). Although this result contradicts the predictions of the job search models, it is confirmed in the different models and for the different measures of overeducation. The positive sign might therefore illustrate the effect of professional experience in reducing overeducation (Rubb, 2003). If we consider that overeducation at the beginning of the career may be related to a lack of skills (Chevalier, 2003), then taking a job earlier after graduation allows the individuals to accumulate more experience and potential on-the-job training to compensate.

^{***}indicates significance at the 1% level.

^{**}at the 5% level.

^{*}at the 10% level.

Our main focus is on the effect of migration (or spatial mobility) on overeducation. The results are presented in Tables 3 and 4. Overall, we find a significant and negative effect of migration on both dimensions of mismatch, although the effect is stronger on statistical overeducation than on subjective mismatch. This suggests that increasing the job search radius and looking for opportunities on a national (rather than local) level can be a good strategy for young workers to avoid overeducation. Interestingly, this finding partially contradicts the work of Devillanova (2013), who does not find any significant effect of migration on the risk of overeducation for Italian workers when controlling for selection and endogeneity biases. However, the author finds that commuting improves the match between education and job. Similarly, Meliciani and Radicchia (2016) observe no effect of migration on overeducation, except for specific geographical areas in Italy. On the contrary, our findings are in line with the studies conducted by Jauhiainen (2011) on Finnish data and Ramos and Sanromá (2013) on Spanish data, which both observe that moving to another region reduces the risk of overeducation for workers. Also on Spanish data, Romaní et al. (2016) confirm the link between spatial mobility and overeducation only for some specific groups as the highly educated, while Croce and Ghignoni (2015) show a negative impact of commuting on the risk of educational mismatch for Italian upper-secondary graduates, as well as a negative impact of migration for university graduates. These results support the need for an analysis that differentiates between education levels, as is done in Table 6.

6.2 | Differentiation by migration and educational level

Tables 5 and 6 present the effects of our four variables of interest, differentiating between migration to all regions and migration to Paris. Table 5 provides results for the whole population, while Table 6 provides results for different educational levels.⁷

Results of our various estimated models reveal that the coefficients for migration to Paris are approximately four to six times higher than for migration to all regions. This finding suggests that the Paris region is particularly advantageous for young people seeking jobs that match their skill levels. The higher job density and various job opportunities in Paris likely enable individuals to search more effectively for well-suited positions. In addition, previous studies like Combes et al. (2012) have demonstrated that wages in the Paris region are 24% higher than those in the rest of France, and a significant part of this wage premium is attributed to the higher skills of the Parisian workforce. The successful matching of skills demanded and offered by employers in Paris may contribute to these higher wages. Furthermore, considering that highly qualified individuals are less likely to be overeducated and that Paris attracts and concentrates a large number of highly skilled individuals, it is quite logical to observe such a strong effect of migration to Paris. Other studies, such as Büchel and van Ham (2003), Jauhiainen (2011) and Ramos and Sanromá (2013), also have similar conclusions, showing that residing in larger labour markets is beneficial as it reduces the probability of overeducation. More generally, previous research has highlighted that the effects of migration may vary depending on the destination. For instance, studies like Meliciani and Radicchia (2016) or lammarino and Marinelli (2015) have found contrasting effects for Italian workers migrating to the north or south of the country.

Finally, Table 6 presents the effects of spatial mobility on overeducation, considering the educational level and migration destination. We show that the negative effect observed for the whole sample varies significantly depending on the educational level. Specifically, individuals with at least a 5-year degree are less likely to be statistically overeducated when they migrate. However, we do not find any significant effect of residential migration on subjective mismatch. This may indicate that spatial mobility allows workers to find better-matched jobs, but the costs associated with migration lead them to underestimate its benefits, resulting in a self-assessed mismatch. Venhorst and Cörvers (2018) also find that the effects of spatial mobility on subjective evaluations may differ depending on the educational level. For college graduates, they observe the negative effects of migration on subjective job-match

⁷For the sake of clarity and because the effects of the other variables are similar to those obtained in Tables 3 and 4, we report only the coefficients for migration in the table. Full tables are available upon request.

TABLE 5 Linear probability models - Effects of migration.

·						
	Statistical o	vereducation				
	All migration	ns		Migrations	to Paris	
	OLS	Heckman	Heckman + IV	OLS	Heckman	Heckman + IV
Coefficient	-0.038***	-0.038***	-0.072***	-0.023***	-0.023***	-0.572***
Standard error	0.009	0.009	0.017	0.006	0.006	0.099
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Job characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.251	0.251	0.250	0.250	0.250	0.161
	Subjective	mismatch				
	All migration	ons		Migrations	s to Paris	
	OLS	Heckman	Heckman + IV	OLS	Heckman	Heckman + IV
Coefficient	-0.015	-0.015	-0.046**	0.007	0.006	-0.247**
Standard error	0.010	0.010	0.019	0.004	0.004	0.102
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Job characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.074	0.074	0.073	0.074	0.074	0.054
Observations	12,968	12,962	12,962	12,968	12,962	12,962

Note: Standard errors are clustered by region. OLS = ordinary least squares.

Source: Authors' calculations based on Génération 2010 data.

measures. Conversely, they find a positive effect of migration on subjective evaluations of job-match quality for university graduates. While our analysis confirms some differentiated effects, it contradicts their conclusion as we do not find any significant effects of migration for the most educated or the least educated individuals. We only report some negative effects on the risk of subjective mismatch for 3-year university graduates. These differences in results may be attributed to the contrasting economic and institutional contexts in the Netherlands and France.

In addition, our findings suggest that 2-year university graduates do not seem to benefit from migration in any dimension of mismatch. On the contrary, we observe significant negative effects of spatial mobility (both national migration and migration to Paris) for individuals with intermediate tertiary education (3- and 4-year degrees). This result is consistent with Croce and Ghignoni (2015), who find that moving (by relocation) decreases the risk of a wrong match for more educated graduates but has little or no effect on the least educated ones. Only commuting time appears to be helpful for this latter category. Similarly, in the Spanish case, Romaní et al. (2016) evidence that migration has no effect on overeducation, except for male workers with a university degree. On Dutch data, Venhorst and Cörvers (2018) find a positive effect of internal migration on the likelihood of obtaining a horizontal match for both college and university graduates. However, the authors considered movers on both short and long distances. In fact, the mean distance moved was between 20 and 30 km, according to the population studied. It is, therefore, difficult to compare these mobilities with inter-regional migrations that take place over several hundred kilometres (as is the case for France, Italy or Spain).

^{***}indicates significance at the 1% level.

^{**}at the 5% level.

^{*}at the 10% level.

TABLE 6 Linear probability models - Effects of migration by educational level.

	Statistical ov	vereducation					
	All migration	าร		Migrations t	o Paris		
Degree	Two-year	Three-year or more	Five-year or more	Two-year	Three-year or more	Five-year or more	
Coefficient	-0.023	-0.102***	-0.102***	-0.432	-0.601***	-0.461***	
Standard error	0.021	0.026	0.032	0.301	0.117	0.121	
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes	
Job characteristics	Yes	Yes	Yes	Yes	Yes	Yes	
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	
R-squared	0.33	0.211	0.162	0.297	0.099	0.066	
	Subjective r	nismatch					
	All migration	ns		Migrations t	o Paris		
Degree	All migration	Three-year or more	Five-year or more	Migrations t Two-year	Three-year or more	Five-year or more	
Degree Coefficient		Three-year	•		Three-year	•	
-	Two-year	Three-year or more	or more	Two-year	Three-year or more	or more	
Coefficient	Two-year -0.007	Three-year or more -0.062**	or more -0.049	Two-year -0127	Three-year or more -0.248**	or more -0.228*	
Coefficient Standard error	Two-year -0.007 0.024	Three-year or more -0.062** 0.028	or more -0.049 0.035	Two-year -0127 0.340	Three-year or more -0.248** 0.117	or more -0.228* 0.129	
Coefficient Standard error Individual characteristics	Two-year -0.007 0.024 Yes	Three-year or more -0.062** 0.028 Yes	or more -0.049 0.035 Yes	Two-year -0127 0.340 Yes	Three-year or more -0.248** 0.117 Yes	or more -0.228* 0.129 Yes	
Coefficient Standard error Individual characteristics Job characteristics	Two-year -0.007 0.024 Yes Yes	Three-year or more -0.062** 0.028 Yes Yes	or more -0.049 0.035 Yes Yes	Two-year -0127 0.340 Yes Yes	Three-year or more -0.248** 0.117 Yes Yes	or more -0.228* 0.129 Yes Yes	

Note: Standard errors are clustered by region. Estimated coefficients are those obtained with our model controlling for selection and endogeneity biases (Heckman procedure + instrumental variables).

Source: Authors' calculations based on Génération 2010 data.

Overall, we find that the results by educational level are qualitatively similar, whether considering only migrations to Paris or all inter-regional migrations: spatial mobility mainly benefits more educated workers. However, interestingly enough, we find that subjective mismatch is reduced only by migrations to Paris for the 5-year university graduates (although the effect is significant only at the 10% level) but not by other residential migrations. This might be the sign that the most educated value some advantages specifically associated with living in the capital city. Regarding statistical overeducation, on the contrary, we find similar coefficients for the intermediate and highest tertiary education graduates for general migration, while the effect is relatively lower for the most educated looking at migration to Paris (but still much higher than the effect of any inter-regional migration). Because overeducation can be related to a lack of job opportunities, it may seem logical that this problem mainly concerns the highly educated. Indeed, they may need to be close to large metropolitan areas (like Paris) to find suitable jobs. On the contrary, jobs corresponding to shorter university education may be less concentrated in specific regions, reducing the importance of being mobile to find a matched job. For the less educated, increasing daily commutes might then be sufficient to avoid being overeducated.

^{***}indicates significance at the 1% level.

^{**}at the 5% level.

^{*}at the 10% level.

6.3 | Robustness checks

6.3.1 | Model specification

In our work, migrations are defined by a dummy variable indicating whether or not young people have changed the region at the end of their studies. The main limitation of our approach is that moving from a region to a neighbouring region and moving to a region far away are considered similar. In some cases, it is a move of a 100 km or so, while in others, it could be much greater. Then, we propose to compute the migration distance in kilometres when a change of region is observed. Because we do not have detailed information for the initial place of residence and the current place at the time of the survey, we cannot use more precise distances. Results of estimated models with this alternative measure for migrations are summarized in Table 7.

Considering distances, rather than the simple fact of moving or not, yields slightly different results. We still highlight a negative effect of migration on the risk of overeducation: the greater the distance, the lower the risk. Moving to a distant place would be considered only for a job that corresponds to the young people's skill level. It is a clear observation when we focus on the statistical measure. In addition, we confirm the fact that the most educated are the first to benefit from such mobility. In line with our previous models, estimations based on the subjective measure of overeducation reveal some differences depending on the educational level. We find that migrations are helpful for young people with at least a 3-year university degree. However, if the effect for the 5-year university graduates is now significant, it is only at the 10% level. Therefore, it is important to consider this result with caution.⁹

When examining subjective mismatch, one can consider that the offered wage for the job is an important omitted variable. Individuals are more likely to feel mismatched when they are offered low-paying jobs rather than well-paid ones. This could introduce bias if the wage variable is correlated with other explanatory variables in our model. However, due to limited information on wages in the Génération 2010 survey, we chose not to include it in our baseline model. For robustness checks, estimations including wages are still presented in Appendix E (Table E2). Interestingly, while including wages has no effect on the significance of the effect of migration on statistical overeducation, it does have an impact on subjective mismatch. It emphasizes the need for caution when interpreting results from estimations that do not control for wages offered. The divergence in results between the two types of mismatch may illustrate both the actual differences they measure and potential biases in subjective approaches. It is possible that respondents mistake educational or skill mismatch with other factors, such as lower wages, as suggested by Hartog (2000).

6.3.2 | Estimation strategy and dependent variable

In our main analysis, we estimate our models in two steps, using a Heckman procedure (Heckman, 1979) to control for selection and then using 2SLS and instrumental variables in linear probability models to control for the endogeneity of migration. Two main limitations may result from such a specification. Firstly, the use of linear probability models can lead to predicted probabilities outside the [0;1] interval. Secondly, employment and migration can result from a joint decision and thus be correlated. To take both these issues into account, we use a triprobit model to estimate the three equations (employment, migration and mismatch) simultaneously. Tables E3 and E4 (in Appendix E) present the estimated coefficients of the model. As these coefficients do not represent marginal effects, their orders of magnitude cannot be discussed.

With this alternative estimation strategy, we still observe that health status has a significant impact on employment probability (column 1). Concretely, having a long-lasting health problem remains negatively associated with the

⁸The distance is a Euclidian distance between the centroids of the region.

⁹Verifying the nonlinearity of migration distances could be a relevant question. However, the need to calculate the logarithm of this variable (due to the distribution of this variable expressed in kilometres) does not allow us to do it in our model.

1435997, 2023, 5. Downholed from https://sicoinnect.online/https://sic

TABLE 7 Linear probability models - Effects of migration (measured in km).

	Statistical ov	Statistical overeducation			Subjective mismatch	nismatch		
Degree	All	Two-year	Three-year or more	Five-year or more	All	Two-year	Three-year or more	Five-year or more
Log (migration distance in km)	-0.013***	-0.011***	-0.013***	-0.017***	-0.007**	0.003	-0.011^{**}	-0.010*
Standard error	0.003	0.004	0.004	0.005	0.003	0.004	0.005	900.0
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Job characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.250	0.330	0.213	0.162	0.073	0.109	0.047	0.045
Observations	12,962	4892	8059	5410	12,962	4892	8059	5410

Note: Standard errors are clustered by region. Estimated coefficients are those obtained with our model controlling for selection and endogeneity biases (Heckman procedure

**at the 5% level.

⁺ Instrumental variables).

^{***}indicates significance at the 1% level.

^{*}at the 10% level.

likelihood of finding a job. In addition, most of our independent variables show the expected signs. Specifically, women with children are less likely to be employed. This could be attributed to the challenges of balancing family and professional life, especially when the child is at an early age. Living with parents also has a negative effect on employment probability, which may be due to young people having fewer financial constraints in this living arrangement. We also find that obtaining a higher diploma decreases the chances of being employed at the time of the survey. This could indicate a more selective job search, with individuals seeking well-paid positions or roles that align better with their personal expectations. It is important to consider that the field of study may significantly influence the chances of finding a job, with graduates from health or education studies being the most advantaged.

Concerning migration (column 2), the decision seems to be linked to some demographic characteristics such as age or having children. People living alone are more likely to migrate as they are more autonomous in their decision-making. The most educated (5-year degree or more) are also the most inclined to migrate, which is consistent with the assumption that their job search is longer and more intense. Moreover, this equation confirms the necessity to consider past migration to explain recent moving. Whether it is a voluntary inter-regional migration or a mandatory stay abroad during studies, a positive and significant influence is shown.

Results relating to the equation for risk of overeducation (column 3) are in a straight line with our linear probability models (see Table 3). In particular, we confirm that migration (or spatial mobility) helps to reduce the chances of being mismatched. The effect, significant at the 1% level, is then robust to the estimation method retained. Most interesting, the parameters ρ represent the correlation coefficient between the errors of each of the three probits. As the parameter ρ_{23} is statistically significantly different from zero at the 5% level, the two probits (for migration and overeducation) have to be estimated jointly. In this case, running simple probits may give biased results. It also confirms the fact that the migration decision is endogenous to the risk of overeducation. On the contrary, the parameter ρ_{13} associated with probits for employment and overeducation shows that we cannot reject the null hypothesis that the errors are uncorrelated. Therefore, the two equations could be estimated separately. This observation is not surprising as the inverse Mills ratio was only significant at the 10% level in Table 3. This does not mean that these equations are uncorrelated, but it could indicate that the data are consistent with no selection.

Finally, even if we propose two different measures of overeducation (the statistical and subjective ones), they appear to be complementary. To ensure that our results are not related to the measure retained, we use an alternative measure of statistical overeducation, based on the median and quartiles of the distribution. We consider that there is an educational mismatch for the levels farthest from the median. Therefore, an individual is considered overeducated if their level of schooling is higher than the third quartile of the distribution of education in their particular occupation. Results for our main estimated models are presented in Appendix E (Table E1). We find a negative and significant effect in the same order of magnitude as the one observed for our first statistical measure. The effects of most of the other independent variables are in line with those previously obtained.

7 | CONCLUSION

The aim of this study was to examine the impact of spatial mobility on the risk of overeducation among young workers. We focused specifically on how residential migration affects their likelihood of experiencing job mismatches, with a particular emphasis on migration to Paris and the educational attainment of individuals. For this analysis, we mobilized data from the Génération 2010 survey conducted by Céreq, which allowed us to explore both statistical overeducation and subjective mismatch. To address potential biases, we employed the Heckman procedure to account for self-selection into employment and retained an instrumental variables approach to address the endogeneity of migration. Our findings remained robust even after considering these two potential issues.

We show that individuals who change their region of residence between graduation and their current job (observed 3 years later) have a lower likelihood of being overeducated, based on both the statistical and subjective definitions of mismatch. We find that this negative effect is particularly pronounced for those who migrate to Paris,

confirming the attractiveness of this area with its abundance of job opportunities. We also find that spatial mobility does not provide an advantage for all young workers. Specifically, it does not significantly reduce the risk of overeducation for 2-year university graduates. On the contrary, 3- and 4-year university graduates experience a reduction in their risk of overeducation after migration.

In terms of public policy recommendations, these findings support measures or programmes aimed at improving workers' mobility. Encouraging or promoting inter-regional migrations of young people appears to be an efficient strategy, as it is associated with a lower risk of job mismatch. It is particularly relevant for this category as the costs associated with migrations might be limited compared to some others. Young people are indeed often renters, single and without children (or with young children), making residential relocation more feasible for them. However, for other categories, higher financial and psychological costs might discourage mobility.

It is also important to consider that individuals' migrations are often motivated by the desire to be closer to job opportunities. Therefore, it would be beneficial to develop regions or territories that are suffering from a lack of such opportunities. By increasing the attractiveness of these regions (for firms or economic activities), it becomes easier to facilitate better job matching in the local labour markets. This recommendation is in line with the literature on agglomeration effects developed by Duranton and Puga (2004), as well as recent research such as the one by Berlingieri (2019). The author demonstrates that workers in large cities are less likely to be overqualified for their jobs and more likely to work in the field for which they were trained. In addition, Venhorst et al. (2010) showed that migration between peripheral regions (as opposed to economic centres) is not marginal and does not concern only the least-able graduates but might not be exclusively related to work-related reasons (see also Bernela & Bonnal, 2022). This implies that, in economies showing this centre-periphery geography of labour markets, these attractiveness policies may be needed to ensure a correct match between jobs and workers. This question, in the French context, should nevertheless be examined to convince of the necessity of such a policy. It must be the issue for future research on qualification and educational mismatches.

ACKNOWLEDGEMENTS

The authors would like to thank two anonymous referees for their useful suggestions and comments, as well as participants in the 20th International Workshop on Spatial Econometrics and Statistics, the 70th Congress of the French Economic Association, the 63rd New Zealand Association of Economists Annual Conference, the Winter School on Public Policy Evaluation 2022 and the ERUDITE and GAINS seminars for their comments on this paper.

DATA AVAILABILITY STATEMENT

Programmes to permit replication can be provided, but we are not allowed to share the data used in this manuscript. Access can be granted by the Adisp (French National Archive of Data from Official Statistics) upon request at http://www.progedo-adisp.fr/enquetes_travemp.php.

ORCID

Florian Fouquet https://orcid.org/0000-0002-5833-4973

REFERENCES

Allen, J., & van der Velden, R. (2001). Educational mismatches versus skill mismatches: Effects on wages, job satisfaction, and on-the-job search. Oxford Economic Papers, 53, 434–452. https://doi.org/10.1093/oep/53.3.434

Andersson, M., Klaesson, J., & Larsson, J. P. (2014). The sources of the urban wage premium by worker skills. *Papers in Regional Science*, 93, 727–747. https://doi.org/10.1111/pirs.12025

Baert, S., Cockx, B., & Verhaest, D. (2013). Overeducation at the start of the career: Stepping stone or trap? *Labour Economics*, 25, 123–140. https://doi.org/10.1016/j.labeco.2013.04.013

Baert, S., & Verhaest, D. (2019). Unemployment or overeducation: Which is a worse signal to employers? *De Economist*, 167, 1–21. https://doi.org/10.1007/s10645-018-9330-2



- Banerjee, S., Chatterji, P., & Lahiri, K. (2017). Effects of psychiatric disorders on labor market outcomes: A latent variable approach using multiple clinical indicators. *Health Economics*, 26, 184–205. https://doi.org/10.1002/hec.3286
- Barnay, T. (2020). Interactions of work and health: An economic perspective. In T. Theorell (Ed.), *Handbook of socioeconomic determinants of occupational health*. Springer.
- Bell, D., & Blanchflower, D. (2011). Young people and the great recession. Oxford Review of Economic Policy, 27, 241–267. https://doi.org/10.1093/oxrep/grr011
- Berlingieri, F. (2019). Local labor market size and qualification mismatch. *Journal of Economic Geography*, 19, 1261–1286. https://doi.org/10.1093/jeg/lby045
- Bernela, B., & Bonnal, L. (2022). Mobilités géographiques et relation formation-emploi: Une analyse longitudinale de l'enseignement supérieur français. *Revue Économique*, 73, 695–733. https://doi.org/10.3917/reco.735.0695
- Blanchflower, D., & Freeman, R. (2000). The Declining Economic Status of Young Workers in OECD countries. In D. Blanchflower & R. Freeman (Eds.), Youth Unemployment and Joblessness in Advanced Countries. University of Chicago Press. https://doi.org/10.7208/chicago/9780226056845.001.0001
- Büchel, F., & Battu, H. (2003). The theory of differential overqualification: Does it work? *Scottish Journal of Political Economy*, 50, 1–16. https://doi.org/10.1111/1467-9485.00251
- Büchel, F., & van Ham, M. (2003). Overeducation, regional labor markets, and spatial flexibility. *Journal of Urban Economics*, 53, 482–493. https://doi.org/10.1016/S0094-1190(03)00008-1
- Chevalier, A. (2003). Measuring over-education. *Economica*, 70, 509–531. https://doi.org/10.1111/1468-0335.t01-1-00296
- Combes, P.-P., Duranton, G., & Gobillon, L. (2015). Workers and wages in the greater Paris region. Revue Économique, 66, 317–350. https://doi.org/10.3917/reco.pr2.0039
- Combes, P.-P., Duranton, G., Gobillon, L., & Roux, S. (2012). Sorting and local wage and skill distributions in France. *Regional Science and Urban Economics*, 42, 913–930. https://doi.org/10.1016/j.regsciurbeco.2012.11.003
- Croce, G., & Ghignoni, E. (2012). Demand and supply of skilled labour and overeducation in Europe: A country-level analysis. Comparative Economic Studies, 54, 413–439. https://doi.org/10.1057/ces.2012.12
- Croce, G., & Ghignoni, E. (2015). Educational mismatch and spatial flexibility in Italian local labour markets. Education Economics, 23, 25–46. https://doi.org/10.1080/09645292.2012.754121
- DaVanzo, J., & Morrison, P. A. (1981). Return and other sequences of migration in the United States. *Demography*, 18, 85–101. https://doi.org/10.2307/2061051
- Davia, M. A., McGuinness, S., & O'Connell, P. J. (2017). Determinants of regional differences in rates of overeducation in Europe. *Social Science Research*, 63, 67–80. https://doi.org/10.1016/j.ssresearch.2016.09.009
- Détang-Dessendre, C. (1999). Reciprocal link between exit from unemployment and geographical mobility. *Environment and Planning a: Economy and Space*, 31, 1417–1431. https://doi.org/10.1068/a311417
- Détang-Dessendre, C., Drapier, C., & Jayet, H. (2004). The Impact of Migration on Wages: Empirical Evidence from French Youth. *Journal of Regional Science*, 44, 661–691. https://doi.org/10.1111/j.0022-4146.2004.00353.x
- Devillanova, C. (2013). Over-education and spatial flexibility: New evidence from Italian survey data. *Papers in Regional Science*, 92, 445–464.
- Di Paolo, A., Matas, A., & Raymond, J. L. (2017). Job accessibility and job-education mismatch in the metropolitan area of Barcelona. *Papers in Regional Science*, 96, 91–112. https://doi.org/10.1111/pirs.12179
- Dolton, P., & Vignoles, A. (2000). The incidence and effects of overeducation in the UK graduate labour market. *Economics of Education Review*, 19, 179–198. https://doi.org/10.1016/S0272-7757(97)00036-8
- Duncan, G. J., & Hoffman, S. D. (1981). The incidence and wage effects of overeducation. *Economics of Education Review*, 1, 75–86. https://doi.org/10.1016/0272-7757(81)90028-5
- Duranton, G., & Puga, D. (2004). Micro-foundations of urban agglomeration economies. In J. V. Henderson & J.-F. Thisse (Eds.), *Cities and geography*. Elsevier. https://doi.org/10.1016/S1574-0080(04)80005-1
- Faggian, A., & McCann, P. (2008). Human capital, graduate migration and innovation in British regions. *Cambridge Journal of Economics*, 33, 317–333. https://doi.org/10.1093/cje/ben042
- Fahr, R., & Sunde, U. (2006). Spatial mobility and competition for jobs: Some theory and evidence for Western Germany. Regional Science and Urban Economics, 36, 803–825. https://doi.org/10.1016/j.regsciurbeco.2006.05.001
- Frank, R. H. (1978). Why women earn less: The theory and estimation of differential overqualification. *American Economic Review*, 68, 360–373.
- Ghosh, S., & Grassi, E. (2020). Overeducation and overskilling in the early careers of PhD graduates: Does international migration reduce labour market mismatch? *Papers in Regional Science*, 99, 915–944. https://doi.org/10.1111/pirs.12509
- Greenwood, M. J. (1997). Internal migration in developed countries. In M. R. Rosenzweig & O. Stark (Eds.), *Handbook of Population and Family Economics Volume 1*. Elsevier. https://doi.org/10.1016/S1574-003X(97)80004-9
- Hartog, J. (2000). Over-education and earnings: Where are we, where should we go? *Economics of Education Review*, 19, 131–147. https://doi.org/10.1016/S0272-7757(99)00050-3



- Heckman, J. J. (1979). Sample selection bias as a specification error. Econometrica: Journal of the Econometric Society, 47, 153–161. https://doi.org/10.2307/1912352
- Hensen, M. M., De Vries, M. R., & Cörvers, F. (2009). The role of geographic mobility in reducing education-job mismatches in the Netherlands. *Papers in Regional Science*, 88, 667–682. https://doi.org/10.1111/j.1435-5957.2008.00189.x
- lammarino, S., & Marinelli, E. (2015). Education-job (mis)match and interregional migration: Italian university graduates' transition to work. *Regional Studies*, 49, 866–882. https://doi.org/10.1080/00343404.2014.965135
- Jauhiainen, S. (2011). Overeducation in the Finnish regional labour markets. *Papers in Regional Science*, 90, 573–588. https://doi.org/10.1111/j.1435-5957.2010.00334.x
- Langella, M., & Manning, A. (2022). Residential mobility and unemployment in the UK. Labour Economics, 75, 102104. https://doi.org/10.1016/j.labeco.2021.102104
- Lemistre, P., & Moreau, N. (2009). Spatial mobility and returns to education: Some evidence from a sample of French youth. Journal of Regional Science, 49, 149–176. https://doi.org/10.1111/j.1467-9787.2008.00574.x
- Meliciani, V., & Radicchia, D. (2016). Informal networks, spatial mobility and overeducation in the Italian labour market. *The Annals of Regional Science*, 56, 513–535. https://doi.org/10.1007/s00168-016-0752-y
- Meroni, E., & Vera-Toscano, E. (2017). The persistence of overeducation among recent graduates. *Labour Economics*, 48, 120–143. https://doi.org/10.1016/j.labeco.2017.07.002
- Nauze-Fichet, E., & Tomasini, M. (2002). Diplôme et insertion sur le marché du travail: Approches socioprofessionnelle et salariale du déclassement suivi d'un commentaire de Saïd Hanchane et Eric Verdier. *Econ Stat*, 354, 21–48. https://doi.org/10.3406/estat.2002.7383
- Olea, J. L. M., & Pflueger, C. (2013). A robust test for weak instruments. *Journal of Business & Economic Statistics*, 31, 358–369. https://doi.org/10.1080/00401706.2013.806694
- Pissarides, C. A., & McMaster, I. (1990). Regional migration, wages and unemployment: Empirical evidence and implications for policy. Oxford Economic Papers, 42, 812–831. https://doi.org/10.1093/oxfordjournals.oep.a041980
- Ramos, R., & Sanromá, E. (2013). Overeducation and local labour markets in Spain. Tijdschrift voor Economische en Sociale Geografie, 104, 278–291. https://doi.org/10.1111/j.1467-9663.2012.00752.x
- Romaní, J., Casado-Díaz, J., & Lillo-Banuls, A. (2016). On the links between spatial variables and overeducation. *Applied Economics Letters*, 23, 652–655. https://doi.org/10.1080/13504851.2015.1095996
- Rubb, S. (2003). Overeducation: A short or long run phenomenon for individuals? *Economics of Education Review*, 22, 389–394. https://doi.org/10.1016/S0272-7757(02)00052-3
- Rumberger, R. W. (1981). The rising incidence of overeducation in the US labor market. *Economics of Education Review*, 1, 293–314. https://doi.org/10.1016/0272-7757(81)90001-7
- Rupert, P., & Wasmer, E. (2012). Housing and the labor market: Time to move and aggregate unemployment. *Journal of Monetary Economics*, 59, 24–36. https://doi.org/10.1016/j.jmoneco.2011.10.008
- Schmutz, B., Sidibé, M., & Vidal-Naquet, E. (2021). Why are low-skilled workers less mobile? The role of mobility costs and spatial frictions. Annals of Economics and Statistics, 142, 283–304. https://doi.org/10.15609/annaeconstat2009.142.0283
- Sicherman, N., & Galor, O. (1990). A theory of career mobility. *Journal of Political Economy*, 98, 169–192. https://doi.org/10. 1086/261674
- Simpson, W. (1992). Urban structure and the labour market: Worker mobility, commuting and underemployment in cities. Clarendon Press.
- Stock, J., & Yogo, M. (2005). Testing for weak instruments in linear IV regression. In D. W. Andrews (Ed.), Identification and inference for econometric models: Essays in honor of Thomas Rothenberg. Cambridge University Press. https://doi.org/10.1017/CBO9780511614491.006
- Tsang, M., Rumberger, R., & Levin, H. (1991). The impact of surplus schooling on worker productivity. *Industrial Relations*, 30, 209–228. https://doi.org/10.1111/j.1468-232X.1991.tb00786.x
- van Ham, M. (2001). Workplace mobility and occupational achievement. *International Journal of Population Geography*, 7, 295–306. https://doi.org/10.1002/ijpg.225
- Venhorst, V. A., & Cörvers, F. (2018). Entry into working life: Internal migration and the job match quality of higher-educated graduates. *Journal of Regional Science*, 58, 116–140. https://doi.org/10.1111/jors.12347
- Venhorst, V. A., van Dijk, J., & van Wissen, L. (2010). Do the best graduates leave the peripheral areas of the Netherlands? Tijdschrift voor Economische en Sociale Geografie, 101, 521–537. https://doi.org/10.1111/j.1467-9663.2010.00629.x
- Verdugo, R., & Verdugo, N. (1989). The impact of surplus schooling on earnings: Some additional findings. *Journal of Human Resources*, 24, 629–643. https://doi.org/10.2307/145998
- Vornholt, K., Villotti, P., Beate, M., Bauer, J., Colella, A., Zijlstra, F., Van Ruitenbeek, G., Uitdewilligen, S., & Corbière, M. (2018). Disability and employment—Overview and highlights. *European Journal of Work and Organizational Psychology*, 27, 40–55. https://doi.org/10.1080/1359432X.2017.1387536
- Wooldridge, J. (2002). Introductory econometrics: A modern approach. South-Western Cengage Learning.

How to cite this article: Fouquet, F., & Sari, F. (2023). Spatial mobility and overeducation of young workers: New evidence from France. *Papers in Regional Science*, 102(5), 945–983. https://doi.org/10.1111/pirs.12755

APPENDIX A: STATISTICAL OVEREDUCATION MEASURE

TABLE A1 Correspondence of educational levels between classifications.

Educational levels	Isced	RNCP
Five-year tertiary degree and higher	Isced 7 and 8	RNCP 7 and 8
Three- or four-year tertiary degree	Isced 6	RNCP 6
Two-year tertiary degree	Isced 5	RNCP 5
General high school	Isced 3 (General) and 4	RNCP 4
Vocational high school	Isced 3 (Vocational)	RNCP 4
Short vocational high school	Isced 3 (Vocational)	RNCP 3
No degree	Isced 0, 1 and 2	-

Note: Isced = International standard classification of education; RNCP = Répertoire national des certifications professionnelles, French classification of education and degrees.

TABLE A2 Correspondence of occupational levels between classifications.

PCS	Isco	Occupations
32	Isco 2 except 24 and 25	Science, health, teaching and cultural professionals
36	Isco 1, 24 and 25	Managers and business and administration professionals
41	Isco 32	Health and teaching associate professionals
46	Isco 33, 34 and 35	Business and administration associate professionals
47 and 48	Isco 31	Technicians
51	Isco 4* and 5*	Public sector workers
54 and 55	Isco 4 and 52	Clerical support and sales workers
56	Isco 51, 53 and 54	Personal service workers
61	Isco 7 and 8	Blue-collar skilled workers
66	Isco 9	Blue-collar unskilled workers
69	Isco 6	Agricultural workers

Note: Isco = International standard classification of occupations. PCS = Professions et catégories socio-professionnelles, Occupations and socioprofessional categories. *Occupations in PCS 51 are similar to those in PCS 54, 55 and 56 but in the public sector.

TABLE A3 Occupation-degree correspondence grid – Statistical overeducation.

	32	36	41	46	47-48	51	54-55	56	61	66	69
Five-year tertiary degree and higher	Ν	Ν	OE	OE	OE	OE	OE	OE	OE	OE	OE
Three- and four-year tertiary degree	Ν	Ν	N	OE	OE	OE	OE	OE	OE	OE	OE
Two-year tertiary degree	Ν	Ν	N	Ν	N	OE	OE	OE	OE	OE	OE
General high school	Ν	Ν	Ν	Ν	N	OE	OE	OE	OE	OE	OE
Vocational high school	Ν	Ν	Ν	Ν	N	OE	OE	OE	OE	OE	OE
Short vocational high school	Ν	Ν	Ν	Ν	N	Ν	N	Ν	Ν	Ν	Ν
No degree	Ν	Ν	N	N	N	N	N	N	Ν	N	N

Note: Undereducation is labelled here as normal, N = normal; OE = overeducation.

APPENDIX B: THE GEOGRAPHY OF FRENCH REGIONS

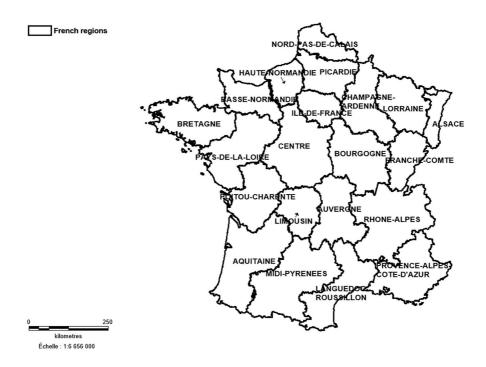


FIGURE B1 French administrative regions.

1435997, 2023, 5. Downholed from https://sicoinnect.online/https://sic

APPENDIX C: DISTRIBUTION OF PREDICTED OVEREDUCATION WITHIN THE SAMPLE

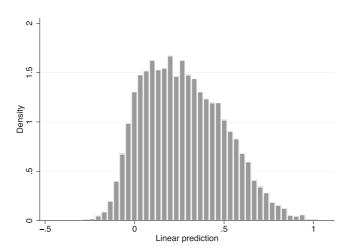


FIGURE C1 Statistical overeducation. Source: Authors' calculations based on Génération 2010 data.

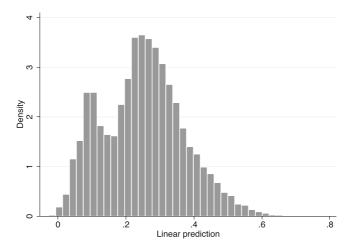


FIGURE C2 Subjective mismatch. Source: Authors' calculations based on Génération 2010 data.



APPENDIX D: SELECTION EQUATION AND FIRST-STAGE REGRESSION FOR 2SLS

TABLE D1 Employment equation and IV estimation (first stage).

	Employment	Migration IV (first stage)
Constant	1.101***	0.687***
	0.107	0.080
Demographic characteristics		
Woman	0.012	-0.005
	0.025	0.007
Age	-0.005	-0.018***
	0.004	0.003
Children	0.022	-0.057***
	0.057	0.011
$Woman \times children$	-0.420***	0.017
	0.046	0.015
Residential status (reference: living alone)		
Living with a partner	0.159***	-0.049***
	0.027	0.008
Living with their parents	-0.492***	-0.135***
	0.047	0.027
Educational level (reference: 2-year degree)		
Three- or four-year degree	-0.221***	0.077***
	0.043	0.019
Five-year degree or more	-0.105**	0.133***
	0.049	0.019
Field of study (reference: services)		
Education	0.526*	0.082
	0.279	0.057
Humanities	-0.175***	-0.002
	0.035	0.012
Economics, business and law	0.018	-0.002
	0.041	0.012
Science	0.106**	0.045***
	0.044	0.015
Industry	0.296***	0.042**
	0.047	0.017
Agriculture	-0.109	0.075**
	0.089	0.030
Health	0.421***	0.081***
	0.081	0.016
		(Continues

1435997, 2023, 5. Downholed from https://sicoinnect.online/https://sic

TABLE D1 (Continued)

	Employment	Migration IV (first stage)
Long-lasting health problems	-0.131***	
	0.045	
Migration during studies		0.413***
		0.052
Study abroad (mandatory)		0.094**
		0.036
Region fixed effects	Yes	Yes
R-squared	0.063	0.263
N	15,865	15,865

Note: Standard errors are clustered by region.

Source: Authors' calculations based on Génération 2010 data.

APPENDIX E: ALTERNATIVE ESTIMATIONS

TABLE E1 Linear probability models for an alternative measure of overeducation

	OLS	Heckman	Heckman + IV
Constant	0.512***	0.357***	0.393***
	0.035	0.038	0.111
Migration	-0.025**	-0.025**	-0.053***
	0.009	0.009	0.015
Demographic characteristics			
Woman	0.037***	0.038***	0.038***
	0.006	0.006	0.007
Age	-0.012***	-0.013***	-0.014***
	0.001	0.001	0.001
Children	0.008	0.015	0.014
	0.006	0.019	0.016
$Woman \times children$	0.006	-0.085***	-0.085***
	0.023	0.023	0.027
Residential status (reference: living alone)			
Living with a partner	-0.007	0.024*	0.022**
	0.009	0.013	0.010
Living with their parents	0.076***	-0.047	-0.052*
	0.011	0.031	0.029

^{***}indicates significance at the 1% level;

^{**}at the 5% level.

^{*}at the 10% level.



TABLE E1 (Continued)

	OLS	Heckman	Heckman + IV
Educational level (reference: 2-year deg	gree)		
Three- or four-year degree	0.118***	0.066***	0.070***
	0.011	0.014	0.016
Five-year degree or more	0.228***	0.207***	0.214***
	0.016	0.014	0.012
Field of study (reference: services)			
Education	0.021	0.126**	0.127**
	0.050	0.056	0.052
Humanities	0.073***	0.025	0.024
	0.014	0.018	0.017
Economics, business and law	-0.006	-0.002	-0.003
	0.014	0.013	0.011
Science	-0.069***	-0.045***	-0.044***
	0.013	0.012	0.013
Industry	-0.040***	0.043**	0.026
	0.014	0.019	0.018
Agriculture	0.139***	0.110***	0.114***
	0.035	0.035	0.024
Health	-0.066***	0.015	0.017
	0.012	0.017	0.022
Business sector (reference: services)			
Public sector	-0.045***	-0.045***	-0.044***
	0.010	0.010	0.007
Agriculture	0.399***	0.397***	0.398***
	0.066	0.066	0.037
Sales	0.168***	0.168***	0.168***
	0.011	0.011	0.011
Construction	0.048*	0.049*	0.049**
	0.027	0.027	0.021
Industry	0.042**	0.043**	0.043***
	0.019	0.019	0.011
Job characteristics			
Working full time	-0.077***	-0.077***	-0.076***
	0.014	0.014	0.010
Permanent job	0.055***	-0.054***	-0.054***
	0.010	0.010	0.007
Time to get first job	0.006***	0.006***	0.006***
	0.001	0.001	0.001
Inverse Mills ratio		0.580***	0.578***

1435997, 2023, 5. Downholed from https://sicoinnect.online/https://sic

TABLE E1 (Continued)

	OLS	Heckman	Heckman + IV
Region fixed effects	Yes	Yes	Yes
R-squared	0.160	0.161	0.160
N	12,968	12,962	12,962

Note: Standard errors are clustered by region.

 $\label{eq:ols} \text{OLS} = \text{ordinary least squares}.$

TABLE E2 Linear probability models including wages.

	Statistical overeducation	Subjective mismatch
Constant	2.655***	1.778***
	0.151	0.166
Migration	-0.062***	-0.033*
	0.018	0.019
Demographic characteristics		
Woman	0.042***	-0.018**
	0.008	0.009
Age	-0.014***	0.007***
	0.002	0.002
Children	0.036**	0.007***
	0.018	0.002
$Woman \times children$	-0.047	-0.074**
	0.031	0.034
Residential status (reference: living alone)		
Living with a partner	0.012	0.036***
	0.011	0.012
Living with their parents	0.049	-0.045
	0.033	0.036
Educational level (reference: 2-year degree)		
Three- or four-year degree	0.252***	0.016
	0.018	0.019
Five-year degree or more	0.128***	0.030**
	0.014	0.015
Field of study (reference: services)		
Education	-0.116**	-0.026
	0.059	0.064
Humanities	-0.055***	-0.009
	0.019	0.021

^{***}indicates significance at the 1% level.

^{**}at the 5% level.

^{*}at the 10% level.



TABLE E2 (Continued)

	Statistical overeducation	Subjective mismatch
Economics, business and law	0.071***	0.018
	0.013	0.014
Science	-0.069***	-0.014
	0.014	0.016
Industry	0.008	0.036
	0.021	0.023
Agriculture	0.096***	-0.054*
	0.027	0.029
Health	-0.139***	-0.069**
	0.025	0.027
Business sector (reference: services)		
Public sector	-0.079***	-0.021**
	0.008	0.009
Agriculture	0.284***	-0.034
	0.044	0.048
Sales	0.210***	0.140***
	0.012	0.014
Construction	0.086***	-0.010
	0.023	0.025
Industry	0.089***	0.065***
	0.013	0.014
Job characteristics		
Wage (In)	-0.298***	-0.237***
	0.013	0.014
Working full time	0.090***	-0.033**
	0.014	0.016
Permanent job	-0.019**	-0.010
	0.008	0.009
Time to get first job	0.004***	0.004***
	0.001	0.001
Inverse Mills ratio	0.298***	0.431***
	0.071	0.160
Region fixed effects	Yes	Yes
R-squared	0.250	0.104

Note: Standard errors are clustered by region. Estimated coefficients are those obtained with our model controlling for selection and endogeneity biases (Heckman procedure + instrumental variables).

 $[\]ensuremath{^{***}}\xspace$ indicates significance at the 1% level.

^{**}at the 5% level.

^{*}at the 10% level.

 TABLE E3
 Employment, migration and overeducation – Triprobit model.

	Employment	Migration	Overeducation
Constant	1.111***	6.753***	1.172***
	0.112	0.261	0.242
Migration			-0.274***
			0.069
Demographic characteristics			
Woman	0.011	-0.021	0.216***
	0.025	0.023	0.024
Age	-0.005	-0.056***	-0.066***
	0.004	0.008	0.007
Children	0.022	-0.179***	0.106
	0.057	0.035	0.087
Woman × children	-0.419***	0.043	-0.049
	0.046	0.055	0.105
Residential status (reference: living alone)			
Living with a partner	0.159***	-0.151***	-0.007
	0.027	0.022	0.034
Living with their parents	-0.492***	-0.563***	0.344***
	0.047	0.091	0.039
Educational level (reference: 2-year degree)			
Three- or four-year degree	-0.222***	0.271***	0.816***
	0.044	0.064	0.055
Five-year degree or more	-0.104**	0.442***	0.342***
	0.048	0.058	0.052
Field of study (reference: services)			
Education	0.526*	0.268	-0.298
	0.278	0.186	0.232
Humanities	-0.175***	-0.001	-0.021
	0.035	0.059	0.076
Economics, business and law	0.018	-0.007	0.163***
	0.041	0.042	0.040
Science	0.106**	0.147***	-0.316***
	0.044	0.050	0.048
Industry	0.296***	0.134**	-0.078*
	0.047	0.058	0.041
Agriculture	-0.109	0.273**	0.329***
	0.089	0.108	0.092
Health	0.421***	0.273***	-1.132***
	0.081	0.054	0.083
Business sector (reference: services)			
Public sector			-0.370***
			0.042



TABLE E3 (Continued)

(Continued)			
	Employment	Migration	Overeducation
Agriculture			0.847***
			0.164
Sales			0.626***
			0.041
Construction			0.193*
			0.115
Industry			0.202***
			0.055
Job characteristics			
Working full time			-0.218***
			0.043
Permanent job			-0.203***
			0.037
Time to get first job			0.020***
			0.003
Long-lasting health problems	-0.128***		
	0.045		
Migration during studies		1.186***	
		0.148	
Study abroad (mandatory)		0.302***	
		0.102	
Region fixed effects	Yes	Yes	Yes
ρ ₁₃	-0.071 (0.113)		
ρ ₂₃	0.096** (0.047)		
ρ_{12}	0.023 (0.020)		
Log pseudolikelihood	-21,096.84		
N	15,864		

Note: Standard errors are clustered by region.

 $[\]ensuremath{^{***}}\xspace$ indicates significance at the 1% level.

^{**}at the 5% level.

^{*}at the 10% level.

	,	• • • • • • • • • • • • • • • • • • • •	
	Employment	Migration	Subjective mismatch
Constant	1.128***	6.773***	-0.881***
	0.102	0.269	0.153
Migration			-0.143***
			0.044
Demographic characteristics			
Woman	0.014	-0.021	0.027
	0.025	0.023	0.026
Age	-0.005	-0.056***	0.014***
	0.004	0.008	0.005
Children	0.020	-0.179***	0.071
	0.055	0.035	0.050
$Woman \times children$	-0.418***	0.044	-0.063
	0.046	0.055	0.083
Residential status (reference: living alone)			
Living with a partner	0.156***	-0.151***	0.044
	0.027	0.022	0.030
Living with their parents	-0.494***	-0.563***	0.084
	0.046	0.091	0.093
Educational level (reference: 2-year degree	e)		
Three- or four-year degree	-0.222***	0.271***	0.077*
	0.044	0.064	0.045
Five-year degree or more	-0.111**	0.442***	-0.052
	0.049	0.059	0.041
Field of study (reference: services)			
Education	0.524*	0.273	-0.109
	0.273	0.182	0.123
Humanities	-0.173***	-0.001	0.073
	0.035	0.059	0.089
Economics, business and law	0.020	-0.008	0.012
	0.041	0.042	0.040
Science	0.106**	0.147***	-0.098**
	0.044	0.050	0.041
Industry	0.296***	0.135***	-0.013
·	0.047	0.057	0.064
Agriculture	-0.106	0.273**	0.090
9	0.088	0.107	0.094
Health	0.419***	0.273***	-0.607***
	0.081	0.054	0.056
Business sector (reference: services)			
Public sector			-0.006
			0.029
			···



TABLE E4 (Continued)

	Employment	Migration	Subjective mismatch
Agriculture			-0.134
			0.126
Sales			0.425***
			0.037
Construction			-0.059
			0.114
Industry			0.171***
			0.064
Job characteristics			
Working full time			-0.143***
			0.038
Permanent job			-0.010
			0.036
Time to get first job			0.018***
			0.003
Long-lasting health problems	-0.153***		
	0.045		
Migration during studies		1.187***	
		0.147	
Study abroad (mandatory)		0.293***	
		0.102	
Region fixed effects	Yes	Yes	Yes
ρ_{13}	0.511* (0.286)		
ρ_{23}	0.075** (0.038)		
ρ_{12}	0.024 (0.019)		
Log pseudolikelihood	-22,097.66		
N	15,864		

Note: Standard errors are clustered by region.

 $[\]ensuremath{^{***}}\xspace$ indicates significance at the 1% level.

^{**}at the 5% level.

^{*}at the 10% level.

DOI: 10.1111/pirs.12755



Resumen. Este artículo examina la influencia de la movilidad espacial en el riesgo de la sobreeducación en jóvenes trabajadores franceses. Se empleó una encuesta que daba seguimiento a una cohorte de jóvenes licenciados que accedieron al mercado laboral entre 2010 y 2013, y los resultados revelan que la migración interregional disminuye el riesgo, estadístico y subjetivo, de la sobreeducación. También se demuestra que la migración a un centro económico como la región de París tiene un efecto negativo aún mayor, y que los trabajadores más formados se benefician más de la movilidad espacial. Estos resultados son robustos en cuanto al control de la autoselección y la endogeneidad de la migración, así como respecto a diversas especificaciones del modelo.

抄録: 本稿では、フランスの若年労働者の教育過剰のリスクに対する空間移動の影響を検討する。2010~2013年に 労働市場に参入した若い卒業生のコホートを追跡する調査の結果から、ある地域から他の地域への移住が(統計的 および主観的な)教育過剰のリスクを減少させることが明らかになった。また、経済の中心地(パリ地方)への移住 は、かなり強い負の影響を及ぼしており、高学歴の労働者は空間的移動からより多くの利益を得ることを示すエビ デンスが得られた。自己選択性と移動の内生性を調整しても、さらにはモデルの様々な仕様に対しても、この結果 には頑健性が認められた。