Intergenerational mobility in education in segregated areas: Evidence from sensitive urban areas in France

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Abstract

Using the 2008 french survey *Trajectoires et Origines*, we aim at determining whether the quality of the residential area significantly contributes to explaining the relationship between parents' and children's education. We considered people living in the same dwelling since adolescence (15 years) and calculated a propensity score to reside in a sensitive urban area. Using a log-linear model, we found two patterns of association that fit-well the data. But, the results indicate that the likelihood for an individual to live in a sensitive area does not significantly contribute to explaining the relationship between parents' and children's education. In a second analysis, we used a logit model, and the results indicate that the effect on children's education is significant, but it explains very few proportions of education variance. We also make a distinction between migrants' children and natives, and the results indicate that neighborhood effects cancel out once controlling for parent's education (only for natives' case). The effects remain significant for migrants' children.

Introduction

According to Stiglitz, education is the main factor that determines future opportunities in adult life. Differences in the level of education between people are thus one of the main causes of income and occupational inequality. Studies on intergenerational mobility in education showed that parent's education is the main determinant of children's educational outcomes. The skills of the second generation (children) depend thus on those of their parent's and their ability to transmit to their children (Borjas, 1992). However, a high correlation between parent's and children's outcomes indicates low intergenerational mobility and does not benefit children from poor families. Children from families with a high level of education will then be more likely to have a high level of education and those from families with a low level of education will be more likely to have a low level of education (Becker, 1981; Goldberger, 1989b). In that case, government intervention is necessary to guarantee equal opportunities to all its population.

Residential segregation is an unequal residential distribution of social groups in urban space (Massey, 1995; Préteceille, 2006). Burgess and Park are the first authors to address spatial segregation and to introduce the word "*urban ecology*" to describe the city organization. They define segregation as the result of a geographical repartition of the city into many areas (business district, residential area, suburbs,...) and found it appropriate to use the word "*specialization of cities*". Indeed, cities are divided into areas according to their amenities. An area with many firms is then more likely to be an industrial city rather than a residential area. But, according to Schelling segregation is not the result of a geographical repartition but the result of many mechanisms including organized discrimination (for example by politics), social differentiation, or the result of combined individual decisions. Sensitive neighborhoods (or neighborhoods in difficulty) are the most visible result of urban segregation (Maurin, 2004). They were defined in France by public authorities to target neighborhoods in difficulty for priority aid. French national statistics found that immigrants, the second generation of immigrants, and modest families are the most predominant people in these areas.

The consequences of immigration in the receiving country depend on how immigrants and their offspring adapt to the labor market (Borjas, 1992). A high concentration of migrants and children of migrants in some sensitive areas is also likely to induce occupational segregation (manual skilled or unskilled jobs). This is one of the main reasons why some studies use the socio-professional category as a measure of segregation index. According to Maurin (2004), "diversity is not really a decisive issue when the neighborhood and the social environment have no effect on destinies. The greater or the lesser importance of diversity for the future of a society is determined by the existence or the absence of context effects". According to Schelling (1971) the choice of the neighborhood is equivalent to choosing neighbors. Poor children living with poor neighbors are then less likely to receive a good education and to escape from poverty (Wilson, 1991; Van Kempen and Şule Özüekren, 1998; Jencks and Mayer, 1990) (due to peer and adults influences) than rich children living with rich neighbors.

In the first paragraph, we presented the results of some studies showing that parent's and children's education are correlated. In the second and third paragraphs, we also presented the results of other studies showing that neighborhoods also influence children's education. The main objective of the analysis is then to show whether neighborhood effects contribute to explain the relation between parent's and children's education. We also aim at determining the explained variance in children's education attributed to parent's education and neighborhood effects.

We used data from the survey *Trajectoires et Origines* carried out in France between 2008 and 2009 and focused on people living in the same neighborhood since they are 16 years. To see whether neighborhoods influence the association between parent's and children's education, we use a log-linear model, mostly used in studies on social mobility. The results obtained showed that even though a link between neighborhood and parent education exists, they do not contribute to explaining the relation between parent's and children's education. Moreover, using a logit model, the results indicate that even though neighborhoods have a significant effect on children's education, they only explain 1.55% of the variance. However, making a distinction between migrants' and native's children, the results indicate that neighborhoods have no significant effect on natives' children's education when we control for their parent's education. But the effects on migrants' children's education remain significant.

The study is organized as follows. In the first two sections, we present the literature review, the data, and descriptive statistics. In section 3, we describe the log-linear modes used and in section 4, we present respectively the results obtained from the log-linear models and the results obtained from the logit model. In section 5, we present the results between natives' and migrants' children.

Context of sensitive urban areas

According to the french law of November 1996, Sensitive Urban Areas (SUA) are "areas characterized by the presence of neighborhoods of degraded habitat and an accentuated imbalance between habitat and employment". Since 2000, the number of sensitive areas in France is estimated to 751, with an average of 6000 inhabitants per area. They represent 7% of the French population in 2006. Young people (those under 25 years) accounted for 39.9% of the SUA's population and reported having difficulty finding a job. The unemployment rate in SUA is relatively high compared to the other neighborhoods. In 2009, the youth unemployment rate in SUA was estimated at 18.6% compared to 9.5% for the whole territory. However, the rise in the unemployment rate cannot be attributed solely to the problem of settlement in these areas. According to the 2005 report of the *Observatoire national des zones urbaines sensibles* residential mobility is higher in SUA compared to other areas (people with well socio-demographic characteristics move outside SUA and those with bad socio-demographic characteristics move inside SUA). However, the inflow of people moving in these areas is more frequent (20%) than that of people who move out. People moving outside SUA are generally native french people.

Since 1894, government housing programs are set up to provide decent housing for modest populations. These housings are owned by the government or the private sector to which the government provides subsidies to reduce the price of rents. However, Verdugo (2011) showed that public housing also tends to increase ethnic and social segregation. The 2006 report of the french national statistics states that 60% of people living in SUA reside in public housing (compared to 20% of other neighborhoods) and 17.5% are foreign-born. For example, the share of immigrants from the Maghreb was estimated at nearly 50% compared to 15% of native French people according to the 1999 census. The poverty rate in 2006 is also twice as high in SUA (29%) as in non-SUA (12%) (the 2010 report of the *observatoire national de la pauvreté et de l'exclusion sociale*).

1 Litterature review

Intergenerational mobility in education focuses on the relationship between parent's and children's education and the mechanisms explaining this relation (Hertz et al., 2007; Checchi et al., 2008). Studies found that South American countries and Southern Europe have low mobility (Blanden, 2013).

Social and economic equality are the main challenges of both developing and developed countries. Although the income gap within and between origin and destination countries are the main cause of people's migration, it is also one of the main causes of income and education inequalities between natives and migrants in receiving countries (Borjas, 1992). However, Card et al. (1998); Bauer and Riphahn (2006); Van Ours and Veenman (2003) found that inequality between natives and migrants declines over generations thanks in part to education and economic systems in the destination country (Bauer and Riphahn, 2006, 2009). On the other hand, the family background takes a great part in explaining inequality within generations (Becker and Tomes, 1979; Dustmann, 2008; Blanden et al., 2004; Solon, 2002). The link between parent's and children's income or education depends on factors such as gender, age, household size, the level of parent's education and income. Children from rich parents are therefore more likely to be rich compared to children from poor families.

Similar to studies on intergenerational mobility, studies on neighborhood effects focused on the economic performance of people such as their level of education or income and their socio-professional category (Garner and Raudenbush, 1991; Kremer, 1997; Sewell and Armer, 1966). They indicate that neighborhoods have significant effects on people's outcomes. Sociologists define 15 mechanisms through which neighborhoods affect the level of education, income, and socio-professional occupation of residents. These mechanisms are grouped into 4 categories including those related to the environment, geography, institutions, and social interactions. Social interactions between individuals may induce changes in attitudes, behaviors, and educational and career aspirations (Jencks and Mayer, 1990; Manski, 1993). For example, Sewell et al. (1957) showed that children from disadvantaged neighborhoods have low educational aspirations compared to those who live in advantageous neighborhoods. On the other hand, institutional and geographical mechanisms affect the economic outcomes of the population through factors such as the geographical location of neighborhoods and the public services therein.

The family characteristics influence not only the intergenerational mobility of a child but also where he lives (Jencks and Mayer, 1990). It is then necessary to distinguish between family and neighborhood effects. Experiments carried out in the USA consisted of randomly distributing families in different neighborhoods. The results indicate no or fewer neighborhood effects

(Kling et al., 2007; Leventhal and Brooks-Gunn, 2003). On the opposite, Kleinepier and van Ham (2017) explained that the residential environment is much more important for the future of children than that of adults and parents used to choose their residential area depending on their endowments and also on those of their future neighborhood. Thomas Schelling's dynamic model of segregation (Schelling, 1971) also posits that people choose to reside in neighborhoods depending on many factors such as income, race, ethnicity...They have a ratio of tolerance toward people outside their group which influences their choice to stay or move to another neighborhood. As a result, residential preferences at the individual level can lead to segregated areas thus attracting people from the same group to these areas. Massey on his model of spatial assimilation of migrants indeed suggested that upon arrival in the destination country, migrants settle in neighborhoods and regions with high rates of migrants to reduce opportunity costs for accommodation and employment. Even though well-endowed families (in terms of skills and earnings) later move outside inner cities, they transmit skills and earnings to the next generation. Focusing on migrants and the second generation of migrants, Borjas (1992) found that taking into account neighborhood effects influences the effect of parental skills and ethnic capital on children's education (Borjas, 1995). Chetty and Hendren (2018) also found that moving from disadvantageous to advantageous neighborhoods (respectively from advantageous to disadvantageous) has significant and positive effects (respectively negative effects) on children's future outcomes. The results are explained by differences between neighborhoods (wealth, employment, and criminality rates).

2 Data and Descriptive Statistics

We used data from the survey "Trajectoires et Origines (TeO)" carried out in France (between 2008 and 2009) by the National Institute for Statistics and Economic Studies (INSEE) and the National Institute for Demographic Studies (INED). The main objective of the survey is to identify the effects of social and ethnic origins on the social and economic trajectories of individuals. Migrants and the second generation of migrants (defined as children born in France from a mother or/and a father born abroad) are the main targets of the survey. Natives are also surveyed.

Social, cultural, and ethnic issues are very sensitive in France. The survey TeO is the most original and global survey that exists in France. Other surveys on migrants and second generation of migrants exist but they are done via insurance funds, firms, or by great organizations such as the European Union(they do not take into account all French regions). They are for example the survey on older immigrants (Cnav2002) and the survey on *The integration of European second generation (Ties)2006.* The second advantage of the survey is that it incorporates data on the residential environment of individuals. Secondly,

The TeO survey is about 21800 individuals including 8200 migrants, 8300-second generation of migrants, 3900 natives, and 1400 individuals from the French overseas territories. We focus the analysis on the second generation of migrants and natives. We restricted the sample to people living in the same neighborhood since the age of 15 years from the question: "Le logement aux

15 ans de l'enquêté est celui qu'il habite aujourd'hui". These people have spent much of their childhood and adolescence in the neighborhood to be sufficiently exposed to the neighborhood effects. Moreover, whether they attended schools of their neighborhood or not, we assume that living in the same neighborhood during childhood or adolescence will significantly influence their educational attainment and also the transmission process of education through peer influences. People may also live in the same neighborhood (for example neighborhood A) until 15 years and go to another neighborhood (neighborhood B) and return to neighborhood A. Therefore, we exclude from our sample people (77 individuals) who have lived in the neighborhood for less than 5 years. We also exclude people who studied abroad. The total sample consists of 2798 individuals aged from 17 to 60 years.

Definition of variables and descriptive statistics (Table1)

Dependent variable: The level of education of the individual: is measured by the highest degree obtained

The variable is grouped in 5 categories: none, primary, undergraduate, high school (equivalent to baccalaureate), and university degree. The primary school degree corresponds to the end of primary school. It was canceled in France in 1989. The undergraduate school degree corresponds to college and post-college certificates such as the certificate of professional skills (*Certificat d'Aptitude professionnelle*) and the Professional Studies Certificate (*Brevet d'études professionnelles.* Descriptive statistics in Table 1 show that 70% of individuals in the sample have at least an undergraduate school degree.

Independent variables

Migration Status of the individual: The main targets of the survey are migrants and the second generation of migrants. The number of the second generation of migrants is then higher than that of natives. We have 2392 individuals born in France with at least one parent born abroad and 495 natives. They represent respectively 82.70% and 17.30% of the sample. The variable is equal to 1 for the second generation of migrants and 0 for natives.

Sensitive urban area (SUA): It is measured by the likelihood to live in a sensitive urban area (P(SUA)). In the absence of data measuring the segregation index, most of the studies on segregation in France used to use the socio-professional category or the unemployment rate in the neighborhood as an indicator of an area segregation(Pan Ké Shon, 2010; Préteceille, 2006).

Even though our analysis is based on people living in the same neighborhood since they were 15 years, we do not have any information on recent developments in their neighborhoods since then. We just have information on the neighborhood characteristics in 2006 (two years before the survey) and information on the socio-professional category of the father or the person who raised the respondent when he was 15 years. Based on neighborhood data in 2006 we then estimated a propensity score i.e the probability for an individual i to live in a given sensitive urban area regardless of his migration status and the duration of residence (details are provided in appendix). Table 1 shows that individuals are on average 24% more likely to live in a sensitive urban area. The result is mainly explained by migrants' children because their likelihood to live in a sensitive area is estimates to (27%) compared to natives children (6%) (Table 12).

By comparing the socio-professional category of the father or the person who raised the respondent when he was 15 years with the probability to live in a sensitive urban neighborhood, the results indicate that children are less likely to live in a sensitive neighborhood as their father occupied a high profession when they were 15 years (Table 2). Likewise, for those whose father occupied an unskilled manual job when they were 15, they are on average 28.89% more likely to live in a sensitive neighborhood. Moreover, Kleinepier and van Ham (2017) found that neighborhood characteristics are stable over time, and using neighborhood measures at one point in time does not lead to biased results. Therefore, using neighborhood characteristics at one point in time (in our case 2006) for people who have lived in the same neighborhood since they are 15 years is a good proxy for the quality of the neighborhood when they were 15 years until their current age. However, an apparent correlation between parental socio-economic status and the quality of the neighborhood where individuals live since they were 15 years could make it difficult to distinguish between the neighborhood effects and family effects. In other terms, which part of children's education is explained by the neighborhood effects and family effects since a family socioeconomic status also determines the quality of residential area?

The level of education of parents: we make a comparison between father's and mother's highest degree obtained and consider only the parent who has the highest degree (for example if the father obtained an undergraduate school degree while the mother obtained a high school degree, we consider only the degree of the mother). Table 1 shows that 33.20% of both parents do not hold a degree but, the result is explained by migrants' children for which 38.51% of both parents have no degree compared to 7.57% for natives. The variable takes the value 1 for children whose parents have no degree, 2 for primary school degree, 3 for undergraduate school degree, 4 for high school degree, and 5 for a university degree.

The Socio-professional category of the father (or the person who raised the individual if the biological father died or is unknown) when the respondent was 15 years: The French National Institute for Statistics and Economic Studies (INSEE) classified workers into 8 socio-professional categories: farmers, artisans traders, and company managers, senior managers and higher intellectual professions, intermediate occupations, employees, manual workers, retirees and people with no professional activity. For people whose father was unemployed or retired at the time of the survey, the previous occupation is considered. Furthermore, we classified and coded socio-professional categories from 1 to 6 (1 for unskilled manual workers, 2 for farmers, 3 for artisans, traders and company managers, 4 for employees and skilled manual workers, 5 for intermediate occupations, and 6 senior managers and higher intellectual professions). The share of people whose father was an unskilled manual worker is equal to 23.30%.

Investments in education made by parents : Becker et al. (2018) and Goldberger (1989a) showed that children's level of education is a function of investments made by parents which is also a function of their income and level of education. We use two variables to measure investments in education made by parents. Firstly, we use a variable indicating whether the respondent (or individual) received additional paid courses during his schooling. Indeed, to increase school results, some parents pay for additional courses for their children. People who received paid courses represent 22.94% of the sample. Secondly, we use a variable indicating whether the individual went to private or public school. Only 4.04% of individuals in the sample always went to private schools.

The proportion of immigrants among pupils at the college where the respondent attended school: In segregated neighborhoods with a high ethnic concentration, and with a high proportion of children going to schools of their neighborhood, the proportion of immigrants among pupils at school is likely to be high. Therefore, a negative correlation between the proportion of immigrant pupils and school resulted in these areas may not be associated with the presence of immigrants pupils, but associated with the social origin of pupils whether there are immigrants or not (the 2017 report of the French Evaluation, Foresight and Performance Direction). But, in all neighborhoods (Whether deprivated neighborhoods or not deprivated), the proportion of immigrants pupils at college may negatively influence the level of education through many mechanisms. First, language difficulties may arise from students of foreign origin leading teachers to spend more time assisting them or to reduce the pace of schooling to the detriment of the other students. Secondly, class cohesion may be negatively affected which may influence class performance. In general, Panza (2020) found that ethnic segregation at school has negative effects on school performance. In the study, the proportion of immigrants among pupils at the college where the respondent attended school is a categorial variable coded from 1 to 5 (with 1 = all of the pupils were of foreign origin, 2= more than half of the pupils were of foreign origin, 3== half of the pupils were of foreign origin, 4= less than half of the pupils were of foreign origin, and 5= barely or none of them was of foreign origin).

Age, gender, and age at the first enrolment at school (including preschool): On average, individuals of the sample are 23 years old and have been enrolled for the first time at school when they were 3 years. The latter variable is included following the study of Bauer and Riphahn (2009) who found that the age at the first entry at school has a significant and positive effect on educational mobility. We also include the variable *gender* as we expect different results for males and females following the study of Schneebaum et al. (2016) who found that the intergenerational mobility of education differs by gender. The variable *gender* is coded 1 for female and 0 for male.

The number of siblings and the number of older siblings with a high school degree: The number of children in a family is likely to have a significant effect on their education. As the number of children increases, investments made in each child decrease (Becker, 1981). However, the number of older siblings with a high school degree is likely to positively influence the level of education of younger siblings as they could consider older siblings as role models of school success. The number of siblings holding a baccalaureate degree is on average equal to 1.

The individual always went to the schools in his sector: the parent's choice to send their children to schools in their neighborhood or another neighborhood is motivated by many reasons including school performance, distance from school to house, or distance from school to their workplace. People who always went to the schools in their neighborhood represents 74.98% of the sample.

The individual believes he has been treated differently from other students during school orientation decisions: In France, school orientations are done after college. Students can then choose their field of study. However, field investigations revealed that some students claimed they have been oriented in a different field of study of their choice (Brinbaum and Primon, 2013). This decision is likely to negatively influence their schooling and even contribute to school drop-out.

The individual lived with both parents (who are still in a relationship) until 18 years: This variable opposes children whose parents are separated (divorced or not) or died. For children whose parents are divorced, theories on marriage and divorce found that the effect on their well-being is negative (Amato and Cheadle, 2005).

Table 1: Descriptive Statistics

Variables	Frequency(%) or Mean	Std.dev (for quantitative variables)	Number of observations
Level of education of the individual			2 798
None degree	10.58		
Primary school degree	0.57		
Undergraduate school degree	34.45		
High school degree	35.74		
University degree	18.66		
Pr (SUA)	.2403528	.3604665	2 770
Migration status			2 798
Children of migrants	82.70		
Natives	17.30		
Gender of the individual			2 798
Female	55.72		
Male	44.28		
Age of the individual	23.18477	6.941954	2 798
Level of education of parents			2 464
None degree	33.20		
Primary school degree	7.63		
Undergraduate school degree	26.83		
High school degree	12.34		
University degree	20.01		
Socio professional category of the father when the individual was 15 years			2 700
Unskilled manual workers	23.30		
Farmers	3.19		
Artisans, traders and company managers	30.33		
Employees and skilled manual workers	21.85		
Intermediate occupations	13.22		

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Variables	Frequency(%) or Mean	Std.dev (for quantitative variables)	Number of observations
Senior managers and higher intellectual professions	8.11		
The individual lived with both parents (still in a relationship) until 18 years			2 798
Yes	90.14		
No	9.86		
Age at first enrolment at school(including preschools)	3.154039	1.179101	2 798
Investments in education made by parents			
The individual received paid courses during his schooling			2 798
Yes	22.94		
No	77.06		
Private or public school			2 798
Alway public schools	73.37		
Always private schools	4.04		
Public and private schools	22.59		
Number of siblings	2.973496	2.844472	2 792
Number of older siblings with a high school degree	1.494492	1.140055	1 634
The individual believes that he has been treated differently from other students in school guidance decisions			2775
Treated better	1.26		
Same treatment	85.23		
Treated less favourably	13.51		
The individual always went to schools in his sector			2 798
Yes	74.98		
No	25.02		
Proportion of immigrants among pupils at the college where the individual attended school			2 747
Almost all were foreign origin	6.44		
More than half were foreign origin	20.09		
Half were foreign origin	25.48		
Less than half were foreign origin	27.34		

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3 r Table 1 – *Continued from previous page*

Variables	Frequency(%) or Mean	Std.dev (for quantitative variables)	Number of observations
Barely or none of them were foreign origin	20.64		

Table 2: Descriptive statistics of propensity score by father's socio-professional category when the respondent was 15 years

Socio-professional categories of the father	Observations	Mean	Std. Dev.	Min	Max
Unskilled manual workers	618	.2889003	.3138123	.0000469	.9010444
Farmers	84	.1136089	.2473195	.0000698	.8580859
Artisans, traders and company managers	795	.2051676	.2840684	.0001154	.9140972
Employees and skilled workers	582	.2092803	.2876036	.0000541	.8994864
Intermediate occupations	348	.110943	.2067955	.0000889	.8804752
Senior managers and higher intellectual professions	211	.072456	.1661744	.0001507	.8393537

3 Model of intergenerational mobility

Many studies used the number of years of schooling to measure intergenerational mobility indice (Hertz et al., 2007; Black, 2011; Black et al., 2005). They generally consider the following model:

$$E_i = \alpha + \beta P_i + \gamma C_i + \epsilon_i \quad (1)$$

Where E_i and P_i are respectively the number of years of studies of an individual and his parent i, C_i is a vector of individual characteristics and family background (age, sex, number of siblings, parents socio-economic status,...). The coefficient β measures the intergenerational elasticity. A high coefficient indicates a high transmission of education from parents to children. Another parameter used to measure intergenerational mobility is the correlation coefficient defined by $\rho = \beta\sigma^p/\sigma^E$ where σ^p and σ^E are respectively the standard deviation of the number of years of schooling of parents and children.

Since the respondent and his parent education data we use are qualitative and categorical, we do not attempt to calculate either the intergenerational elasticity or the correlation coefficient. Instead, we aim at determining the path association between variables. We use a log-linear model (different from a logarithm transformation model used to estimate linear models), typically used in analyses of the intergenerational mobility in occupation (Beck, 1983; Xie and Killewald, 2013; Rosenfeld, 1978; Stevens and Boyd, 1980; Stevens, 1986).

Such models aim at explaining the relationship between many categorical variables. The distinction between dependant and independent variables is not necessary and the model is not defined as a regression model but rather an association model. Our objective is then to determine how the association between respondents' and parent's education depends on the quality of the neighborhood [1]. One of the disadvantages of the log-linear model is that the inclusion of many variables results in more complex models with difficulties of interpretation. Therefore, we limit the analysis to our three main variables and build a multidimensional contingency table (Table 3). The feature of a log-linear model is to find models that fit adequately the data i.e the expected frequencies are not much different from the observed frequencies. By doing so, we can identify the patterns of association between variables.

Considering only the level of education of both parent and children and the quality of the residential environment, let Y_{jkl} and $E(Y_{jkl}) = \mu_{jkl}$ be respectively the observed and the expected frequency of the cell jkl. A log-linear model is specified as follows:

$$log(\mu_{jkl}) = \mu + \alpha_j + \beta_k + \gamma_l \tag{2}$$

For j=1,....5 (for the respondent's education) ; k=1,.....5 (for the parent's education) and l=1,...4 (for the quality of the residential environment)
Where μ is the logarithm of the geometric mean of the expected frequencies of all cells; α_j is the logarithm of the ratio between the geometric mean of the expected frequencies of the cell $j(j = 1, ...5)$ and the geometric mean of the expected frequencies of all cells; β_k is the logarithm of the ratio between the geometric mean of the expected frequencies of the cell $k(k = 1...5)$ and the geometric mean of the expected frequencies of all cells; and γ_l is the logarithm of the ratio between the geometric mean of the expected frequencies of the cell $l(l = 1...4)$ and the geometric mean of the expected frequencies of all cells. In other terms, μ is the global effect, α_j, β_k and γ_l are respectively the effects of variables children's and parent's education and the quality of the residential area.

The equation 2 represents the independence model as it assumes no relationship between the three variables. Using the Deviance Information Criterion (DIC), we test whether this assumption holds. Otherwise, variables are related, and incorporating interaction terms in the independence model improves the goodness-of-fit and leads to models that fit adequately the data. In equation 3, we present a model (called "saturated") that incorporates all interaction terms. Any saturated model fits perfectly the data. So instead of using the saturated model, we look for other models that also fit adequately the data from the independence model by incorporating interaction terms. The results are described in the next section.

$$log(\mu_{jkl}) = \mu + \alpha_j + \beta_k + \gamma_l + (\alpha\beta)_{jk} + (\alpha\gamma)_{jl} + (\beta\gamma)_{kl} + (\alpha\beta\gamma)_{jkl} \tag{3}$$

[1]The variable P(SUA) which is a quantitative variable is divided into subgroups to obtain a categorical variable named "quality of the residential area" and takes the following values: 1:Very high quality for P(SUA) = [0.0000469 - 0.0294503[; 2 : High quality for P(SUA) = [0.0294503 - 0.2014454[; 3: medium quality for P(SUA) = [0.2014454 - 0.332589[and 4:Low quality for P(SUA) = [0.332589 - 0.917709]

Table 3: Multidimensional contingency table (observed frequencies)

		Quality of the residential area				
		Very high	High	Medium	Low	Row total
Respondent's education	Parent' s education					
None	None	33	20	10	61	124
	Primary	7	2	2	4	15
	Undergraduate	29	8	4	15	56
	High school	9	1	0	2	12
	University	5	3	1	1	10
	Column total	83	34	17	83	217
Primary	None	3	1	0	1	5
	Primary	2	1	0	0	3
	Undergraduate	2	1	0	0	3
	High school	1	0	0	0	1
	University	0	0	0	0	0
	Column total	8	3	0	1	12
Undergraduate	None	72	41	21	76	210
	Primary	32	11	3	9	55
	Undergraduate	79	28	9	21	137
	High school	20	8	3	8	39
	University	24	1	1	4	30
	Column total	227	89	37	118	471
High school degree	None	38	19	8	44	109
	Primary	19	8	2	6	35
	Undergraduate	51	21	5	18	95
	High school	17	10	2	9	38
	University	19	9	1	1	30
	Column total	144	67	18	78	307
University degree	None	26	20	6	32	84
	Primary	22	3	1	6	32
	Undergraduate	39	10	7	9	65
	High school	32	9	1	5	47
	University	66	8	2	7	83
	Column total	185	50	17	59	311

4 Results

4.1 Patterns of association between variables

Table 4 presents the results of different log-linear models. The letters in square brackets describe the combinations of variables that have been used to fit the data. We define respondent's education as the dependant variable and parent's education and the likelihood to live in a sensitive area as the independent variables. The deviance criterion is used to select models that fit adequately the data. It is a measure of the goodness-of-fit of models and allows determining how well a model predicts the cell frequencies of the respondent's education according to their parent's education and the quality of a residential area. The deviance follows a chi-squared distribution with γ degrees of freedom. We take 0.05 as a guideline for the level of significance. A significant deviance value indicates that the model does not fit adequately the data and is thus rejected. In other terms, the expected frequencies under that model significantly differ from the observed frequencies.

Model 1 is the independence model in which no relationship between variable is posited, i.e the respondent's education is independent of that of their parent and the quality of the residential area. Models 2 through 4 and 5 through 7 are respectively jointly and conditional independence models. In particular, model 2 assumes that the respondent's education is jointly independent of parent's education and the quality of the residential area. The conditional independence assumption in model 6 is any relationship that may be found between the respondent's education and the quality of the residential area can be explained by the parent's education. Model 8 includes combinations of all effects (except the third-order effect).

The deviance of model 1 is significantly different from zero. The mutual independence hypothesis is then rejected. In other terms, variables are related, and incorporating interaction terms in the independence model is useful. Models 2 through 4 do not also fit the data adequately. The joint independence assumption is then rejected. Concerning the conditional independence models (5 through 7), one of them fits well the data (model 6). Indeed, the result of the model 6 shows that any relationship that may exist between the respondent's education and the quality of the residential area is explained by the parent's education. In other terms, the quality of residential area will have no effect on the respondent's education after controlling for the parent's education. On the opposite, the result of model 7 reveals that any relationship that may exist between respondent's and parent's education can not be explained by the residential area. Model 8 is the homogeneous association model obtained by including all the interaction terms (except for the three-way association). The result indicates that the data is well-fitted using this model.

The feature of the log-linear model is not only to determine models that fit adequately the data but also to determine variables that contribute to increasing the goodness-of-fit of a model. In particular, does the inclusion of the quality of living area in model 8 improves the prediction of the relationship between parent's and individual's education in model 6? Or, is the quality of the living area redundant information in explaining the relationship between parent's and an individual's education?

Table 4: Log-Linear models of the relationship between the quality of the neighborhood, individual's and parent's education

Models number	Models	Deviance goodness-of-fit	Degree of freedom	Prob > chi2
1	[D] [P] [S]	322.5665	75	0.0000
2	[D] [PS]	176.3587	63	0.0000
3	[DP] [S]	192.2472	60	0.0000
4	[DS] [P]	285.1872	64	0.0000
5	[DP] [DS]	155.5467	49	0.0000
6	[DP] [PS]	46.0671	48	0.5524
7	[DS] [PS]	137.9359	52	0.0000
8	[DP] [DS] [PS]	29.76437	37	0.7951

D: repondent's education; P: parent's education; S:P(SUA)
k-order interactions also includes lower order interactions. For example, Model 2 is a first-order interaction thus includes the model1 which has no interaction terms. Model 2: [DP] [PS] is equal to D+P+S+DP+PS

Table 5: Significance tests for association terms

Models number	Association term	χ_2	Degree of freedom	Prob > chi2
Model 1 vs Model 3	DP	130.32	15	0.0000
Model 1 vs Model 4	DS	37.38	11	0.0001
Model 3 vs Model 4	DP/DS	92.94	4	0.0000
Model 3 vs Model 5	DS	36.70	11	0.0001
Model 3 vs Model 6	PS	146.18	12	0.0000
Model 4 vs Model 5	DP	129.64	15	0.0000
Model 5 vs Model 6	DS/PS	109.48	1	0.0000
Model 4 vs Model 7	DP/PS	-17.61	3	1.0000
Model 5 vs Model 8	PS	125.78	12	0.0000
Model 6 vs Model 7	DP/DS	91.87	4	0.0000
Model 6 vs Model 8	DS	16.30	11	0.1303
Model 7 vs Model 8	DP	108.17	15	0.0000

We perform a likelihood ratio test that compares the chi-squared values of models with and without parent's education or the quality of the residential area. When the difference between the chi-squared values of the two models is significantly different from zero, then the introduction of the variable significantly contributes to increasing the prediction of education's frequencies in cells. The results are described in table 5.

They show that including whether DS (association between respondent's education and the quality of the residential area) or DP (association between respondent's and parent's education) in the independence model (model 1 vs model 3 and model 1 vs model 4) contributes to improving the goodness-of-fit of the independence model thus confirming the introduction of interaction terms. Next, we compare the conditional independence models (models 5 through to 7) with the homogeneous association model (model 8). The likelihood ratio between the model 6 and model 8 is not significantly different from zero. In other terms, the association between the respondent's education and the quality of the living area depends on the parent's education. But, for models 7 and 8, the likelihood ratio is significantly different from 0 suggesting that the association between parent's and respondent's education does not depend on the quality of the living area. In short, the introduction of the variable

Some similarities between log-linear and logit models exist. However, the two models are different in the sense that log-linear models describe the joint distribution of all variables while logit models describe the conditional distribution of variables and specify the dependent and the independent variables. Then, in a second analysis, we describe the conditional distribution of the respondent's education. The results are given in the next section.

4.2 Logit model

4.2.1 Effects of neighborhoods and parent's education

Previous studies on neighborhood effects led to mixed results (none, positive or negative effect). The absence of consensus between these studies relies mainly on the method and variables used to estimate neighborhood effects (Jencks and Mayer, 1990). Neighborhood effects can be assimilated to the family effects since neighborhood and family characteristics may be correlated. For example, families with better endowments will reside in high-quality neighborhoods, and those with low endowments will reside in poor neighborhoods. Therefore, we need to distinguish between the neighborhood and family effects. One of the means used by searchers is field experiments. Studies on *Moving to opportunity* experiment in the United States if America found that neighborhoods have no significant effect on adults' outcome (Kling et al., 2007). However, for young children especially those under 13 years, neighborhoods exert significant long-terms effects (Chetty and Hendren, 2018; Chetty et al., 2016). Children's exposure to a high (low) quality neighborhood significantly influences their outcome.

In the absence of field experiments, many studies based their analysis on surveys that collect data at both family and neighborhoods level. Since some family characteristics (income and occupational status, for example) influence the choice of residence, measuring neighborhoods requires identifying family's exogenous influences and the quality of the neighborhood characteristics that matter for children's well-being. The neighborhood's mean income, unemployment rate, ethnic or occupational composition are the most used in literature. Other investigators used different characteristics of neighborhoods to create a composite indicator. However, a composite indicator may not be appropriate from a political point of view to identify the neighborhood characteristics to target.

According to Jencks and Mayer (1990), a mean to test whether neighborhood affects children's well-being is to estimate the effect of a neighborhood indicator with nothing else controlled. Likewise, the way to test whether neighborhood affects children's intergenerational mobility is to estimate the effect of a neighborhood indicator with nothing else controlled. By doing so, we determine the share of outcome variance explained by neighborhood characteristics. Tables 6 and 7 describe the results (people who are current students are not taking into account). On average, the likelihood to reside in a sensitive area significantly influences children's educational attainment (table 6). However, it explains a very few proportions (1.55%) of education variance.

In models 2 through 5 in table 6, we considered some of the neighborhood variables used to estimate the propensity score (fiscal income per consumption unit, the share of people with at least a baccalaureate degree, the proportion of people in higher occupations, and unemployment rate). We found that the fiscal income per consumption unit explains more the education variance than the other variables do.

In table 7 we control for parent education. Even though the effect on children's education is significant and positive, the share of the explained variance in education attributed to parent's education is not high (7.61%). In model 2, the coefficient of the neighborhood (P(SUA)) remains significant, but the coefficient of parent's education declines very slightly. Firstly, We can conclude that neighborhood has less influence on the relationship between parent's and children's education. Secondly, children from low educated parents can then have a high level of education since parent's education does not contribute much in explaining their education. Based on this result, we determine in the next section factors that also influence the educational attainment of people in France.

Table 6: Neighborhood effects on educational attainment

	Model 1	Model 2	Model 3	Model 4	Model 5
P(SUA)	-0.795***				
	(-4.80)				
Fiscal income per consumption unit		0.0508***			
		(7.02)			
The share of people with at least a baccalaureate degree			0.110***		
			(6.92)		
The share of people in senior managers and higher intellectual professions				0.105***	
				(6.49)	
The share of unemployed people (from 15 years old and more)					-0.0960***
					(-5.62)
cut1	-1.813***	-1.235***	-1.174***	-1.158***	-2.250***
	(-23.00)	(-14.07)	(-12.37)	(-11.44)	(-17.15)
cut2	-1.745***	-1.168***	-1.106***	-1.091***	-2.183***
	(-22.36)	(-13.53)	(-11.87)	(-10.96)	(-16.69)
cut3	0.0155	0.608***	0.672***	0.683***	-0.418***
	(0.25)	(7.61)	(7.59)	(7.20)	(-3.51)
cut4	1.053***	1.658***	1.726***	1.733***	0.626***
	(15.23)	(18.68)	(17.82)	(16.93)	(5.18)
Total variance of education	3.342	3.407	3.402	3.388	3.360
Share of explained variance (%)	1.55	3.43	3.29	2.89	2.08
N	1492	1504	1492	1492	1492
Log pseudolikelihood	-2049.8676	-2052.6072	-2036.7099	-2039.7154	-2045.7884
Wald chi2(1)	23.05	49.30	47.94	42.11	31.55
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000
Pseudo R2	0.0057	0.0125	0.0121	0.0106	0.0077

Note: Only regression coefficients are reported.
t statistics in parentheses
* p<0.1, **p<0.05, *** p<0.01

Table 7: Effects of neighborhood and parent's education on educational attainment

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
parent's level of education	0.371***	0.351***	0.325***	0.329***	0.338***	0.346***
	(9.64)	(8.90)	(8.21)	(8.36)	(8.67)	(8.68)
P(SUA)		-0.415**				
		(-2.24)				
The fiscal income per consumption unit			0.0332***			
			(4.18)			
The share of people with at least a baccalaureate degree				0.0791***		
				(4.61)		
The share of people in senior managers and higher intellectual professions					0.0757***	
					(4.36)	
The share of unemployed people (from 15 years and more)						-0.0524***
						(-2.80)
cut1	-0.787***	-0.944***	-0.640***	-0.571***	-0.540***	-1.197***
	(-7.19)	(-7.68)	(-5.48)	(-4.67)	(-4.22)	(-6.72)
cut2	-0.722***	-0.877***	-0.575***	-0.504***	-0.474***	-1.131***
	(-6.64)	(-7.14)	(-4.96)	(-4.16)	(-3.74)	(-6.33)
cut3	1.032***	0.889***	1.193***	1.274***	1.303***	0.636***
	(9.46)	(7.24)	(10.09)	(10.28)	(10.01)	(3.57)
cut4	2.145***	2.007***	2.316***	2.404***	2.431***	1.757***
	(17.61)	(14.95)	(17.60)	(17.51)	(17.01)	(9.46)
Total variance of education	3.561	3.579	3.614	3.627	3.622	3.584
Share of explained variance (%)	7.61	8.07	8.96	9.29	9.17	8.20
N	1330	1319	1330	1319	1319	1319
Log pseudolikelihood	-1795.4291	-1776.6515	-1786.5609	-1768.6092	-1769.6519	-1775.3999
Wald chi2(2)	92.88	96.96	105.43	110.45	107.45	102.19
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Pseudo R2	0.0278	0.0295	0.0326	0.0339	0.0334	0.0302

t statistics in parentheses

* p<0.1, **p<0.05, *** p<0.01

4.3 Determinants of educational attainment in France

Table 8 presents the average marginal effects of an ordered logit model. Moving from the left to the right of the table, we can see that the probability for a child to obtain a high level of education increases as the parents have a high level of education. Children whose parents have a high school degree or a university degree are also more likely to have a high school or a university degree. Furthermore, an increase in the number of older siblings with a baccalaureate degree also increases the likelihood for younger children to have a higher degree. Older siblings are, in a sense, role models (whether negative or positive) for their younger siblings. Having an older sibling with a higher degree may motivate young children to have a higher degree or constitute help for homework. We also found that parent's investments in education significantly increases the probability for children to have a higher degree (except the average variable *the individual received additional paid courses during his schooling* that is not significant). Parent's investments in children's education depend on their income (Conlisk, 1974; Becker et al., 2018; Goldberger, 1989b) that is also a function of their socio-professional category. Children whose fathers were senior managers or occupied higher intellectual professions when they were 15 years are also more likely to have a higher degree. This result is because better-educated parents earn more, value education, and then invest more in their children's education(Becker and Tomes, 1979).

However, when children are more likely to live in a sensitive neighborhood, their chances of having a high school or a university degree decrease. According to the 2013 report of the National Observatory of Sensitive Urban Areas, the school success rate in SUA is lower than the national average. The result is explained by the low level of adults' education in these areas compared to non-deprivated areas. Moreover, if a student feels he has been treated differently during school guidelines, the likelihood to obtain a high school degree significantly decreases. School guidelines are done at the end of college in France. Students can then choose to pursue professional or general training. However, some individuals reported they have been oriented towards professional training while they chose a general training. This result has negative consequences on their schooling since they became less motivated to pursue their studies. As a result, their likelihood to have a baccalaureate and then a university degree significantly decreases. Brinbaum and Primon (2013) found that the feeling of discrimination is more pronounced among descendants of migrants (also see descriptive statistics by migration status in table 12). The results also show that they are less likely to have a higher degree than natives. The share of immigrants pupils at college significantly decreases (only for the modality "less than half of the total pupils") the probability of having a higher degree, which confirms the result of Panza (2020).

Even though Bauer and Riphahn (2006) found that age at first enrollment at school significantly influences the level of education, the result we obtained is not significant. The same is true for variables *number of siblings* and *The individual lived with both parents (still in a relationship) until 18 years.* But, gender and age also significantly influence the level of education of individuals.

Table 8: Determinants of educational attainment: average marginal effects

	Children's highest academic degree				
Variables	**None**	**Primary**	**Undergraduate**	**High school**	**University**
The highest level of education between the two parents (ref. None)					
Primary school degree	-0.0175	-0.000840	-0.0231	0.0177	0.0237
	(-0.87)	(-0.82)	(-0.82)	(0.88)	(0.81)
Undergraduate degree	-0.0322**	-0.00158*	-0.0468**	0.0318**	0.0488**
	(-2.42)	(-1.91)	(-2.39)	(2.39)	(2.40)
High school degree	-0.0419**	-0.00209*	-0.0650**	0.0401***	0.0689**
	(-2.59)	(-1.91)	(-2.33)	(2.66)	(2.28)
University degree	-0.0575***	-0.00294**	-0.0996***	0.0502***	0.110***
	(-3.92)	(-2.36)	(-3.66)	(3.91)	(3.58)
P(SUA)	0.0482***	0.00234**	0.0719***	-0.0414***	-0.0811***
	(2.68)	(2.00)	(2.80)	(-2.76)	(-2.74)
Gender (ref. girls)	-0.0600***	-0.00292**	-0.0895***	0.0516***	0.101***
	(-6.07)	(-2.59)	(-6.97)	(6.02)	(6.79)
Age of the individual	-0.00226***	-0.000110**	-0.00338***	0.00195***	0.00380***
	(-2.77)	(-2.33)	(-2.66)	(2.83)	(2.66)
Migration status(ref.second generation of migrants)	-0.0313**	-0.00152*	-0.0466**	0.0269**	0.0525**
	(-2.45)	(-1.80)	(-2.42)	(2.43)	(2.42)
Lived with both parents until 18 years(ref. yes)	-0.0266	-0.00129	-0.0396	0.0228	0.0446
	(-1.40)	(-1.22)	(-1.42)	(1.41)	(1.41)
Socio-professional category of the father (ref. Unskilled workers)					
Farmers	-0.00603	-0.000294	-0.00881	0.00564	0.00949
	(-0.23)	(-0.23)	(-0.22)	(0.23)	(0.22)
Artisans, traders and company managers	-0.000673	-0.0000325	-0.000952	0.000638	0.00102
	(-0.05)	(-0.05)	(-0.05)	(0.05)	(0.05)
Employees and skilled workers	-0.00903	-0.000441	-0.0134	0.00838	0.0145
	(-0.65)	(-0.63)	(-0.64)	(0.65)	(0.65)
Intermediate occupations	-0.0199	-0.000987	-0.0316	0.0177	0.0348
	(-1.18)	(-1.08)	(-1.12)	(1.19)	(1.11)
Senior managers and higher intellectual professions	-0.0449***	-0.00232**	-0.0844**	0.0328***	0.0988**
	(-2.87)	(-1.99)	(-2.52)	(3.04)	(2.41)
Age at first enrollment at school	0.00702	0.000341	0.0105	-0.00603	-0.0118
	(1.36)	(1.23)	(1.37)	(-1.36)	(-1.37)
Number of siblings	0.00501	0.000243	0.00747	-0.00431	-0.00842
	(1.39)	(1.25)	(1.39)	(-1.39)	(-1.39)
Number of older siblings with a high school diploma	-0.0242***	-0.00117**	-0.0360***	0.0208***	0.0406***
	(-4.93)	(-2.51)	(-5.23)	(4.95)	(5.15)
Investments in education made by parents					
The individual received paid courses during his schooling(ref.yes)	0.0184	0.000893	0.0274	-0.0158	-0.0309
	(1.54)	(1.37)	(1.54)	(-1.54)	(-1.54)
Private or public school (ref. always public school)					
Always private school	-0.0358**	-0.00185*	-0.0676**	0.0238***	0.0814**
	(-2.71)	(-1.90)	(-2.31)	(3.66)	(2.17)
Pubblic and private school	0.00730	0.000352	0.0105	-0.00647	-0.0117
	(0.62)	(0.60)	(0.63)	(-0.61)	(-0.63)
The individual believes that he has been treated differently from other students in school guidance decisions(ref.treated better)					
Same treatment	0.0360	0.00186	0.0686	-0.0234***	-0.0831
	(1.47)	(1.25)	(1.20)	(-2.85)	(-1.10)
Treated less favourably	0.0438	0.00224	0.0798	-0.0302**	-0.0957
	(1.60)	(1.35)	(1.34)	(-2.17)	(-1.23)
The individual always went to the schools in his neighbourhood(ref.yes)	0.0154	0.000739	0.0218	-0.0135	-0.0245
	(1.30)	(1.17)	(1.38)	(-1.28)	(-1.38)
Proportion of immigrants among pupils at the college where the individual attended school(ref.almost all were foreign origin)					
More than half were foreign origin	-0.0322	-0.00150	-0.0408	0.0299	0.0447
	(-1.44)	(-1.31)	(-1.58)	(1.41)	(1.58)
Half were foreign origin	-0.0283	-0.00131	-0.0350	0.0264	0.0381

5 r*Continued on next page*

5 r Table 8 – *Continued from previous page*

	Children's highest academic degree				
	None	**Primary**	**Undergraduate**	**High school**	**University**
	(-1.29)	(-1.19)	(-1.43)	(1.26)	(1.44)
Less than half were foreign origin	-0.0426**	-0.00203	-0.0579**	0.0386*	0.0640**
	(-1.96)	(-1.64)	(-2.30)	(1.86)	(2.34)
Barely or none of them were foreign origin	-0.0304	-0.00141	-0.0381	0.0283	0.0416
	(-1.25)	(-1.14)	(-1.32)	(1.23)	(1.32)
Wald chi2(32)	192.72	192.72	192.72	192.72	192.72
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000
Pseudo R2	0.0548	0.0548	0.0548	0.0548	0.0548
Log pseudolikelihood	-1722.6066	-1722.6066	-1722.6066	-1722.6066	-1722.6066
N	1384	1384	1384	1384	1384

t statistics in parentheses
* p<0.1, ** p<0.05, *** p<0.01

5 Neighborhood effects between natives and migrants' children

Considering the likelihood to live in a sensitive area by ethnic origin, the results in table 12 show that natives have, on average 6.1% chances to live in a sensitive area comparing to 24.7% for migrants' children. Based on this result, we run further regressions to determine whether neighborhoods' effects differ by migration status and, if so, the share of variance explained by neighborhood characteristics. The results are described in table 9 (people who are currently studying are not taking into account). In models 1 and 2 (for migrants' children) and 4 and 5 (for natives' children), we do not control for the family background (age, gender, number of siblings,...). The results show that parent's education and neighborhood have a significant effect on the level of education of migrants' children and natives. Even we control for the family background (in model 3) the neighborhood variable remains significant for migrants' children. However, for natives children in model 6 neighborhood effects cancel out when we control for their parent's level of education. But the p-value for this model is not computed, and we cannot conclude whether all coefficients of the regressions are equal to zero or not. Therefore, we run another regression that does not take into account family characteristics (model 7). The coefficient of the neighborhood becomes non-significant. Therefore, neighborhood quality does not affect natives education once we controlled for parent's education. This result supports that of the log-linear model according to which the effect of the neighborhood cancels out once we control for parent's education.

The share of education variance explained by natives' parent's education is higher (16.86%) than that of migrants' parent's education (8.16%). Therefore, migrants' children are likely to escape from a low level of education since their parents are not only low educated than natives (table 12) but also their level of education does not contribute much to explain their level of education. The implication of the results between natives and migrants' children are the following. Moving a native's child from a non-sensitive area to a sensitive neighborhood will not affect his educational attainment compared to moving a migrant's child to a sensitive area when the parent's education is controlled for. Moreover, migrants' children will benefit from living in a non-sensitive area. In short, sensitive areas hurt foreign communities more than natives communities.

Table 9: Neighborhood effects between natives' and migrants' children

	Migrants' children			Natives			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
P(SUA)	-0.792***	- - - -	-0.790***	-2.314**	- - - -	-0.470	-1.726
	(-4.56)		(-2.97)	(-2.64)		(-0.24)	(-1.22)
parent's level of education							
Primary diploma		0.767***	0.117		1.002**	0.634	0.945**
		(4.03)	(0.42)		(2.35)	(0.94)	(2.18)
Undergraduate diploma		0.343**	0.298		1.279***	0.586	1.201***
		(2.59)	(1.45)		(3.13)	(0.90)	(2.94)
High school diploma		0.871***	0.590		2.512***	0.890	2.393***
		(4.35)	(1.61)		(5.28)	(0.70)	(4.96)
University diploma		1.777***	1.201***		2.590***	0.731	2.557***
		(8.13)	(3.45)		(5.29)	(0.71)	(5.08)
Controlling for family background	*No*	*No*	*Yes*	*No*	*No*	*Yes*	*No*
/							
cut1	-1.799***	-1.218***	-0.724	-2.002***	-0.651*	-6.163**	-0.814**
	(-20.14)	(-12.64)	(-0.63)	(-10.40)	(-1.89)	(-2.06)	(-2.15)
cut2	-1.770***	-1.185***	-0.687	-1.752***	-0.399	-5.596*	-0.558
	(-19.83)	(-12.40)	(-0.59)	(-10.06)	(-1.16)	(-1.86)	(-1.49)
cut3	-0.0326	0.536***	1.123	0.147	1.646***	-2.627	1.483***
	(-0.46)	(6.10)	(0.97)	(1.14)	(4.43)	(-0.88)	(3.79)
cut4	1.039***	1.693***	2.440**	1.047***	2.710***	-1.319	2.558***
	(13.17)	(16.48)	(2.12)	(7.26)	(7.07)	(-0.45)	(6.38)
Total variance of Y	3.347	3.606	4.237	3.385	3.957	6.280	4.019
Share of explained variance (%)	**1.7**	**8.76**	**22.35**	**2.80**	**16.86**	**47.61**	**18.13**
N	1209	1090	624	283	240	111	238
Log pseudolikelihood	-1643.203	-1453.8447	-792.4931	0.0824	-317.30141	-122.53022	-313.74668
Wald chi2()	20.78	79.18	127.34	6.97	41.12	- - - -	44.87
Prob > chi2	0.0000	0.0000	0.0000	0.0083	0.0000	- - - -	0.0000
Pseudo R2	0.0064	0.0314	0.0824	0.0096	0.0642	0.1998	0.0693

Note: Only regression coefficients are reported.
t statistics in parentheses
* p<0.1, **p<0.05, *** p<0.05

Conclusion

Like many studies in intergenerational mobility in education, we aim at determining factors that influence the relationship between parent's and children's education. Some studies have identified factors such as income, investments in education, age at the first entry at school, and the number of siblings (Beck, 1983; Goldberger, 1989b; Bauer and Riphahn, 2006). We also based our analysis on the assumption that the quality of the residential environment significantly contributes to explaining the relationship between parent's and children's education. Studies on the effect of the neighborhood on people's well-being lead to mixed results (no significant and significant effects).

Using the 2008 survey data (that is, mainly focused on migrants' children and natives), we first calculated a propensity score for a given individual to live in a sensitive urban area. Indeed, sensitive urban areas in France are areas with high ethnic and social concentration. Latter, we used a log-linear model to determine the patterns of association between the propensity score and parent's and children's education. The results indicate the likelihood to live in a sensitive area does not significantly contribute to explaining the relationship between parent's and children's education. Moreover, the effect on children's education cancel out when controlling for parent education.

Using another model (logit model) that describes the conditional distribution of the respondent education, we aim at determining whether the neighborhood effect on education is also significant, and, if that is the case, we computed the share of its variance in education. The results indicate that the likelihood to live in a sensitive area has a significant effect on education, but it only explains 1.55% of education variance. We also make a distinction between children of migrants and natives, and the results indicate that, for natives, neighborhood effects cancel out when we control for parent's education. This result confirms that of the log-linear model stating that the effect of the quality of the residential area is not significant after controlling for parent education. On the opposite, neighborhood effect remains significant for migrants' children even after controlling for parent education.

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Appendices

Propensity score

Neighborhoods in France are defined in terms of *IRIS*(Ilots Regroupés pour l'Information Statistique). They are created by the French National Institute for Statistics and Economic Studies for census purposes. They are also derived from an infra-communal division and averaged 2000 inhabitants.

For the survey's anonymizing, neighborhoods are not identified. Only information on the neighborhood characteristics for each individual is provided. We also have information on whether a given individual lives in a sensitive urban area (SUA) in 2008. Based on this information and the neighborhood variables, we calculate a propensity score for an individual i to live in a sensitive neighborhood. The model is given by:

$$P(SUA)_i = \frac{exp(\alpha + \beta_j X_{ij})}{1 + exp(\alpha + \beta X_{ij})} \tag{4}$$

Where X_{ij} is a vector of neighborhood variables for each individual i within an interval of j of the distribution of neighborhood variables. β_j is a vector of neighborhood coefficients. It represents the neighborhood effect of each interval of j of the variable distribution. Since we have 21 neighborhood variables, we only present the distribution of 3 main variables that are widely used in the literature (the unemployment rate, the percentage of people employed in senior managers and higher intellectual professions, and the share of people who got at least a baccalaureate degree). The results are described in table 10. They show that 19.91% of individuals of the sample are in the last decile of the variable "*the percentage of people with at least a baccalaureate*". Moreover, we do not use neither this variable nor the unemployment rate to construct groups of neighborhoods because we assume that an individual who belongs to the last decile of the variable *percentage of people with at least a baccalaureate* may also belong to the last decile of the variable "*unemployment rate*". In other terms, for an individual residing in a neighborhood with a high proportion of people with at least a baccalaureate degree, the unemployment rate in this neighborhood may also be high because of the economic conditions. This is one of the reasons why in the absence of neighborhood identification, we do not construct neighborhood groups based on the distribution of neighborhood variables. We rather group all neighborhood variables and calculate a propensity score for an individual i to live in a sensitive urban area. The results are given in table 11.

Before any interpretation, we test for the performance of the model using a receiver operating curve (ROC, figure 1). The area under the curve (AUC) measures the degree of separability or the goodness of fit of the model. The value of the AUC indicates that our model is able at 94.40% of distinguishing between people living in a sensitive urban area and those living in a non-sensitive area. The results in table 11 show that all variables included in the model significantly influence the likelihood for an individual i to live in a sensitive neighborhood (except for variables "unemployment rate, women unemployment rate, the percentage of people in manual jobs and the percentage of immigrants from Sub Sahara Africa"). In particular, as the individual is in the last distribution (corresponds to higher values) of variables fiscal income per consumption unit, percentage of people in higher occupations, percentage of people with at least a baccalaureate degree, his chances to live in a sensitive neighborhood decrease. On the opposite, the immigrant unemployment rate, the percentage of families for which the reference person is an immigrant, the percentage of people from North African increase the likelihood of an individual to live in a sensitive neighborhood.

Table 10: Distribution of neighborhood variables

Active persons in senior management and higher intellectual professions		Percentage of people with at least a baccalaureate		The youth unemployment rate (15 years and more)	
	Frequency (%)		Frequency (%)		Frequency (%)
Less than 3.3%	6.41	Less than 20.5%	8.41	Less than 4.4%	2.19
From 3.3% to 4.9%	5.92	From 20.5% to 24.0%	6.10	From 4.4% to 5.8%	6.56
From 4.9% to 6.2%	6.48	From 24.0% to 26.8%	6.74	From 5.8% to 6.8%	7.71
From 6.2% to 7.4%	7.27	From 26.8% to 29.3%	7.25	From 6.8% to 7.8%	9.41
From 7.4% to 8.6%	7.99	From 29.3% to 31.9%	7.44	From 7.8% to 8.8%	8.48
From 8.6% to 10.1%	8.57	From 31.9% to 34.7%	7.93	From 8.8% to 9.9%	9.49
From 10.1% to 12.1%	10.27	From 34.7% to 38.1%	10.35	From 9.9% to 11.3%	11.11
From 12.1% to 15.0%	12.03	From 38.1% to 42.5%	12.83	From 11.3% to 13.2%	11.09
From 15.0% to 20.6%	14.80	From 42.5% to 50.3%	13.03	From 13.2% to 16.7%	12.85
20.6% and more	20.26	50.3% and more	19.91	16.7% and more	21.12
Total	100.00	Total	100.00	Total	100.00

Table 11: Average marginal effects (P(SUA)=1)

	average marginal effect	Standard error	T-student	P-value
Fiscal income per consumption unit	-0.00543***	.0010197	-5.322727	1.02e-07
Percentage of active persons in non-standard employment	0.00717***	.0015965	4.489885	7.13e-06
Percentage of active persons in management and al	-0.00470***	.0015995	-2.94139	.0032674
Percentage of active persons in manual work.	-0.000180	.0015124	-.1189385	.9053241
Percentage of single-parent families	0.00987***	.0024229	4.074059	.0000462
Percentage of people with at least a baccalaureate	-0.00810***	.0018361	-4.412088	.0000102
Percentage of households with at least five members	0.00299**	.0012888	2.321959	.0202351
Housing density	0.0104***	.0025064	4.150879	.0000331
Percentage of public housing	0.00512**	.002542	2.015268	.0438766
Percentage of new neighbors	-0.00447**	.0021651	-2.065051	.0389182
Percentage of people who have left the municipality for less than 5 years	-0.0271**	.0136767	-1.983988	.0472572
Percentage of sedentary persons	-0.0282**	.0136549	-2.067765	.0386621
Percentage of immigrants from Sub-Saharan Africa	0.00137	.0015818	.8667156	.3860979
Percentage of immigrants from North Africa	0.00418*	.0025275	1.655146	.0978948
Percentage of immigrants from South Europe (Italia, Spain and Portugal)	-0.0129***	.0018844	-6.849918	7.39e-12
Percentage of immigrants from European Union (Italia, Spain and Portugal are excluded)	-0.00994***	.0020539	-4.83827	1.31e-06
Percentage of families whose reference person is immigrant	0.0140***	.0024207	5.799551	6.65e-09
Youth unemployment rate (15 years and more)	-0.00589	.004417	-1.33433	.1820956
Women unemployment rate (15 years and more)	0.00145	.0036722	.3943371	.6933322
Percentage of unemployed people for over a year	-0.00247**	.0012423	-1.987234	.0468965
Immigrant unemployment rate	0.00995***	.0022502	4.423027	9.73e-06
Wald chi2(21)	475.03			
Prob > chi2	0.0000			
Pseudo R2	0.5015			
N	11802			

* p<0.05, ** p<0.01, *** p<0.001

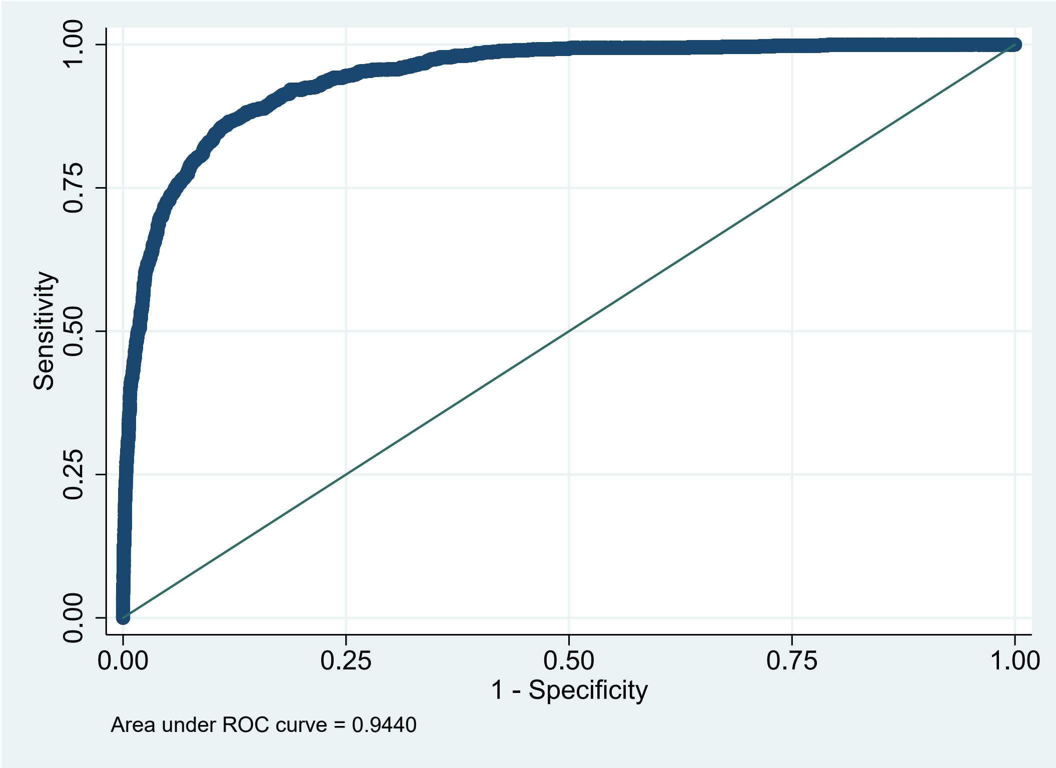

Figure 1: Receiver Operating Characteristic (ROC) curve (for (SUA)

Table 12: Descriptive statistics by migration status

Variables	Descendants of migrants	Std.dev (for quantitative variables)	Natives	Std.dev (for quantitative variables)
Level of education of individuals				
None	10.89		9.09	
Primary school degree	0.30		1.86	
Undergraduate school degree	33.75		37.81	
High school degree	36.43		32.44	
University degree	18.63		18.80	
Gender of the individual				
Female	54.93		59.50	
Male	45.07		40.50	
Age of the individual	22.71478	5.837242	25.43182	10.4775
Level of education of parents				
None	38.51		7.57	
Primary school degree	6.52		13.00	
Undergraduate school degree	25.09		35.22	
High school degree	11.17		17.97	
University degree	18.72		26.24	
Socio professional category of the father				
Unskilled workers	25.56		12.55	
Farmers	1.93		9.15	
Artisans, traders and company managers	31.97		22.55	
Employees and skilled workers	21.48		23.62	
Intermediate occupations	11.75		20.21	
Senior managers and higher intellectual professions	7.31		11.91	
The individual lived with both parents (still in a relationship) until 18 years				
Yes	90.32		10.74	
No	9.68		89.26	
Age at first enrolment at school(including preschools)	3.111495	1.10676	3.357438	1.461134

1 c2r*Continued on next page*

Variables	Descendants of migrants	Std.dev (for quantitative variables)	Natives	Std.dev (for quantitative variables)
Number of siblings	3.183629	2.990898	1.968944	1.671418
Number of older siblings with a high school degree	1.544803	1.182716	1.200837	.7895319
Investments in education made by parents				
The individual received paid courses during his schooling				
Yes	22.13		26.86	
No	77.87		73.14	
Private or public school				
Alway public school	76.53		58.26	
Always private school	2.77		10.12	
Public and private school	20.70		31.61	
The individual believes that he has been treated differently from other students in school guidance decisions				
Treated better	1.00		2.49	
Same treatment	83.74		92.31	
Treated less favourably	15.26		5.20	
The individual always went to schools in his neighbourhood				
Yes	76.06		69.83	
No	23.94		30.17	
Proportion of immigrants among pupils at the college where the individual attended school				
Almost all were foreign origin	7.61		0.85	
More than half were foreign origin	23.48		3.81	
Half were foreign origin	27.62		15.22	
Less than half were foreign origin	26.56		31.08	
Barely or none of them were foreign origin	14.73		49.05	
Pr(SUA	.2779656	.3794186	.0613593	.1565723

Table 13: List of Variables

Individual and family variables	Neighborhood variables
The highest degree obtained by the individual	Fiscal income per consumption unit
The highest degree obtained by parents (we compared the highest degree of both parents and we only considered the parent who got the highest degree)	Percentage of active persons in non-standard employment
The father socio-professional category	Percentage of active persons in senior managers and higher intellectual professions.
Individual's gender	Percentage of active persons in manual works
Individual's age	Percentage of single-parent families
Migration status of individual	Percentage of people with at least a baccalaureate
A dichotomous variable indicating whether the individual lived with both parents until the majority (18 years)	Percentage of households with at least five members
The number of siblings	Housing density
The number of siblings with a baccalaureate degree	Percentage of public housing
The age of individual at first enrollment at school	Percentage of new neighbors
A dichotomous variable indicating whether the individual received additional paid courses	Percentage of people who have left the municipality for less than 5 years
The proportion of immigrants at the college he attended	Percentage of sedentary persons
	Percentage of immigrants from Sub-Saharan Africa
	Percentage of immigrants from North Africa
	Percentage of immigrants from South Europe (Italia, Spain and Portugal)
	Percentage of immigrants from European Union (Italia, Spain and Portugal are excluded)
	Percentage of families whose reference person is immigrant
	The youth unemployment rate (15 years and more)
	The women unemployment rate (15 years and more)
	Percentage of unemployed people for over a year
	The immigrants unemployment rate