WRONG ORIGIN OR WRONG NEIGHBORHOOD: EXPLAINING LOWER LABOR MARKET PERFORMANCE OF FRENCH INDIVIDUALS OF AFRICAN ORIGIN[1]

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1 Introduction

To what extent are lower levels of wages and employment of immigrants descendants due to the fact that they are more likely to live in relatively deprived areas? A first fact is that workers of foreign national origin do not perform as well as native workers. In 2005, there was a 15% differential in the monthly wage and a 15 pp. differential in employment probability between French individuals with French parents and French individuals with parents born with an African nationality. A second fact is that workers living in distressed areas experience more difficulties on the labor market than workers living anywhere else. Comparing French workers living inside "Zones Urbaines Sensibles"[2](ZUS) with French workers outside, there was a 20% wage differential and a 15% differential in employment probability in 2005. Finally, a third fact is that there is a statistical correlation between living in a distressed area and being of foreign origin: 24% of second-generation migrants of African origin live in ZUS areas, versus 6% of French workers of French origin. The question we raise in this paper is: beside composition effects, are there specific factors explaining the lack of performance of foreign-origin workers on the labor market that would be linked with residence location?

Discrimination against minority groups has been extensively studied by economists and econometricians for more than fifty years. Becker (1957), Phelps (1972), Arrow (1973) are pioneering theoretical works that encompassed both taste and statistical discrimination. Empical evidence of discrimination[3] have been provided by roughly two kinds of methods, each one with assets and drawbacks. Audit studies [4] have been developed to experimentally control for all characteristics but the one on which discrimination is to be tested. These audit studies have been used in all kinds of markets (labor, housing, cars...) to detect discrimination against different groups (women, Blacks, immigrants, older workers...) and have proved useful to provide clear evidence about the existence of the phenomenon. Heckman (1998) however formulated critiques against this technique, claiming that focusing on a single case does not prove formally the existence of discrimination in the whole market and that some unobservables would always not be controlled for. Thus, evidence based on indirect approaches remain useful to detect and quantify discrimination.

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[2]"Zone Urbaine Sensible" is a label created in 1996 by the national government in order to signal which areas should be targeted by national or local social and economic programs. The vast majority of the 700 existing ZUS spread over the French territory suffers from high unemployment, high poverty, low education rates.

[3]A comprehensive survey over the empirical literature about discrimination is available in Altonji & Blank (1999).

[4]Riach & Rich (2002) provides an interesting survey of this large literature.

Decomposition techniques, in particular, have been extensively used since their introduction by Blinder (1973) and Oaxaca (1973). This kind of approach obviously suffer from the fact that all variables uncorrelated with the controlled variables but correlated with the fact to belong to the potentially discriminated group may be suspected to bias the results. In the French case, studies dealing with discrimination on the labor market against French individuals of African origin started only recently, mostly because of the lack of data.[5]

Employers may discriminate against workers on the grounds of their (supposed) ethnic groups or their colors, but they may also discriminate against workers living in particularly distressed areas. This kind of discrimination of sometimes named redlining.[6] Even apart from direct discrimination, there exists at least three kinds of reasons to explain lower performance for individuals living in distressed and segregated areas. Obviously, a part of labor performance differentials comes from composition effects as residence location is endogenous and thus depends on individual and household characteristics. Then, the *spatial mismatch* hypothesis, first postulated by Kain (1968), states that the distance to jobs impedes workers living in enclaves to perform as well in the labor market as workers living closer to areas where economic activity is concentrated.[7] Gobillon, Magnac & Selod (2007) and Gobillon & Selod (2008) provide empirical evidence of the relevance of spatial mismatch in the case of Paris region. *Human capital externalities*, as described by Cutler & Glaeser (1997) and Borjas (1998), may also play a role. If residential segregation implies that low-skilled workers are separated from high-skilled ones, spillover effects may take place. In this case, people living in the enclave interact only with low-skilled workers and lose from this segregation.

The idea to try and disentangle consequences of discrimination from those of segregation is not new. Early works by John Kain, in which the concept of spatial mismatch is developed, aims at explaining why Blacks, that mostly stayed in distressed inner cities while Whites and most of the economic activity were fleeing to the suburbs, were experiencing such high levels of poverty and joblessness. In a study comparing Chicago and Los Angeles metropolitan areas, Leonard (1987) finds that residential segregation strongly influences black employment patterns. Holzer & Reaser (2000) and Raphael, Stoll & Holzer (2000) use firm-level data to assess that firms located in suburbs are more likely to discriminate against Blacks. In a first attempt to disentangle residence location effects from discrimination in the French case, Aeberhardt et al. (2009) introduced in the traditional Blinder-Oaxaca decomposition framework crossed dummies for belonging to a ZUS and to the Paris region and found no real evidence of the importance of location to explain the wage and the employment gap.

This study goes one step further and uses the cluster-sampling scheme of the Labor Force Survey to control more accurately for the individuals' neighborhoods of residence. The idea is to identify the within-sampling-area wage and employment gaps between individuals with French parents and individuals with parents born with an African citizenship.[8] An employment model and a wage model are estimated with cluster effects. Then, a three-component decomposition of the employment- and wage-gaps across parents' nationality is introduced.

[5]See, e.g., Silberman & Fournier (1999), Dupray & Moullet (2004), Domingues Dos Santos (2005), Meurs, Pailhé & Simon (2006), Aeberhardt, Fougère, Pouget & Rathelot (2009).

[6]A model of redlining in the labor market close in spirit to statistical discrimination models may be found in Zenou & Boccard (2000) or Zenou (2002). Redlining may also refer to some kind of discrimination in the access to mortgage loans; see, e.g., Tootell (1996).

[7]See Wasmer & Zenou (2002), Smith & Zenou (2003) and Selod & Zenou (2006) for more theoretical details on spatial mismatch and Gobillon, Selod & Zenou (2007) for a well-documented survey.

[8]Maurin (2004) took advantage of the LFS cluster-sampling structure to separate the within-area and the between-area components of social segregation.

When no cluster effects are included in the model, most of the wage gap is explained by differences in individual characteristics while most of employment differential remains unexplained. Surprisingly, the inclusion of cluster effects does not alter dramatically the picture. In particular, two thirds (around 10 percentage points) of the employment gap is still unexplained, even when the influence of residence location is controlled for. This result is all the stronger that the component relating to the differences in cluster effects potentially captures, beside direct neighborhood effects (spatial mismatch, human capital spillovers...), some redlining-discrimination and, most of all, the sorting of individuals with respect to their unobserved productive characteristics. The figure of 10 percentage points of unexplained gap in employment probability is thus an lower bound.

Next section presents the method that will be used to decompose the gap in the labor market outcomes between the two groups. Section 3 details the data and provides some summary statistics. In section 4, the results of the estimations and the decompositions are displayed and discussed.

2 Methodology

2.1 Model

We specify a model of employment as in Gronau (1974) and of wage as in Mincer (1958). The sample is segmented into demographic groups j. We denote E_{ij} the employment status of the individual i in group j and w_{ij} her log-wage.

$$\begin{cases} E^*_{ij} = Z_i\gamma_j + \eta_{a_i} + \varepsilon_{ij} \\ w_{ij} = X_i\beta_j + \alpha_{a_i} + u_{ij} \end{cases}$$

Worker i is employed if and only if $E_{ij} = 1$ (*i.e.* $E^*_{ij} > 0$). She is not employed if and only if $E_{ij} = 0$ or (*i.e.* $E^*_{ij} < 0$). a_i is the neighborhood to which individual i belongs. η_a and α_a are unobservable area-specific effects. Wage is only observed if the worker is employed.

2.2 Decompositions

Empirical evidence of wage and employment discrimination towards workers of foreign origin is established through the decomposition method initiated by Oaxaca (1973) and Blinder (1973). In what follows, population F is assumed to be the reference (*i.e.* not discriminated and majoritary) population whereas population D is the potentially discriminated (*i.e.* minoritary) population.

For a given distribution $G(.)$ of the error in the employment model, the employment probability for an individual i belonging to group j will be:

$$\mathbb{E}(E_i|Z_i, a_i, j) = G(Z_i\gamma_j + \eta_{a_i})$$

Exact decomposition is possible in this framework. The raw employment gap may be split into three terms.

$$
\begin{aligned}
&\underbrace{\mathbb{E}_{A_F}\left(\mathbb{E}_{Z_F|a}\left[\mathbb{E}\left(E_i|Z_i,a_i,j=F\right)\right]\right)-\mathbb{E}_{A_D}\left(\mathbb{E}_{Z_D|a}\left[\mathbb{E}\left(E_i|Z_i,a_i,j=D\right)\right]\right)}_{\text{raw gap}}=\\
&\underbrace{\mathbb{E}_{A_F}\left(\mathbb{E}_{Z_F|a}\left[\mathbb{E}\left(E_i|Z_i,a_i,j=F\right)\right]\right)-\mathbb{E}_{A_D}\left(\mathbb{E}_{Z_F|a}\left[\mathbb{E}\left(E_i|Z_i,a_i,j=F\right)\right]\right)}_{\text{neighborhood quality gap}}\\
&+\underbrace{\mathbb{E}_{A_D}\left(\mathbb{E}_{Z_F|a}\left[\mathbb{E}\left(E_i|Z_i,a_i,j=F\right)\right]\right)-\mathbb{E}_{A_D}\left(\mathbb{E}_{Z_D|a}\left[\mathbb{E}\left(E_i|Z_i,a_i,j=F\right)\right]\right)}_{\text{characteristics gap}}\\
&+\underbrace{\mathbb{E}_{A_D}\left(\mathbb{E}_{Z_D|a}\left[\mathbb{E}\left(E_i|Z_i,a_i,j=F\right)\right]\right)-\mathbb{E}_{A_D}\left(\mathbb{E}_{Z_D|a}\left[\mathbb{E}\left(E_i|Z_i,a_i,j=D\right)\right]\right)}_{\text{unexplained gap}}
\end{aligned}
$$

In these expressions, Z_j (resp. A_j), with $j \in \{D, F\}$ denotes the distribution of the Z's (resp. the a's) in the population j.

Simple empirical counterparts of the following terms can be found:

$$
\begin{aligned}
(1/N_j)\sum_{i\in j} E_i &\overset{p.s.}{\rightarrow} \mathbb{E}_{A_j}\left(\mathbb{E}_{Z_j|a}\left[\mathbb{E}\left(E_i|Z_i,a_i,j\right)\right]\right)=\mathbb{E}[E_{ij}]\\
(1/N_D)\sum_{i\in D}\Phi\left(Z_i\hat{\gamma}_F+\hat{\eta}_{a_i}\right) &\overset{p.s.}{\rightarrow} \mathbb{E}_{A_D}\left(\mathbb{E}_{Z_D|a}\left[\mathbb{E}\left(E_i|Z_i,a_i,j=F\right)\right]\right)
\end{aligned}
$$

with N_D the number of individuals in population D and N_F the number of individuals in population F.
The term $\mathbb{E}_{A_D}\left(\mathbb{E}_{Z_F|a}\left[\mathbb{E}\left(E_i|Z_i,a_i,j=F\right)\right]\right)$ is more difficult to obtain as it involves the distribution of the Z's for population D and the distribution of the η's for population F. Using iterated expectations,

$$
\mathbb{E}_{A_D}\left(\mathbb{E}_{Z_F|a}\left[\mathbb{E}\left(E_i|Z_i,a_i,j=F\right)\right]\right)=\sum_a\sum_Z \mathbb{E}\left(E_{iF}|Z,a\right)p_F(Z|a)p_D(a)
$$

with $p_D(.)$ the density of the sampling units in population D and $p_F(.|a)$ the density of the characteristics in population F conditional on the sampling unit a.

An empirical counterpart for this quantity is then:

$$
\frac{1}{N_D}\sum_{i\in D}\frac{1}{N_F^{a_i}}\sum_{j\in F\cap a_i}\Phi\left(Z_j\hat{\gamma}_F+\hat{\eta}_{a_i}\right)
$$

with $N_F^{a_i}$ the number of F people who reside in the sampling unit a_i.

Note that the decomposition that is proposed here is not unique. However, if the estimation of the model on the sample of the potentially discriminated population is to be avoided, there are only two decompositions left: one involving $\mathbb{E}_{A_D}\left(\mathbb{E}_{Z_F|a}\left[\mathbb{E}\left(E_i|Z_i,a_i,j=F\right)\right]\right)$ and the other one involving $\mathbb{E}_{A_F}\left(\mathbb{E}_{Z_D|a}\left[\mathbb{E}\left(E_i|Z_i,a_i,j=F\right)\right]\right)$. The first one is preferred as its empirical counterpart is easier to compute.

The same reasoning applies for the decomposition of the wage differentials, replacing E by w, with $G(.)$ equal to the identity function.

2.3 Estimation strategies

Estimating parameters of the employment equation requires using panel binary model methods. As the full MLE is known to be biased (due to the incidental parameter problem), we have to rely on alternative techniques. Conditional logit is efficient to differentiate out fixed effects and consistently estimate γ, see Rasch (1960), Andersen (1970), Chamberlain (1980). The only problem with this method is that it does not provide estimates for fixed-effects. We propose a method to retrieve them.

First, conditional logit estimation is used to provide for a consistent $\hat{\gamma}$. We also estimate corresponding standard errors.

In a second stage, we compute the fixed effects of the selection equation. We use the logit assumption to write the log-likelihood. Because the global log-likelihood is additively separable across the neighborhoods a, we can re-write the global problem as a chain of sub-problems. Hence, for all a, maximizing the log-likelihood

$$\ell(\eta_a) = \sum_{i \in a} E_{ia}(Z_i\hat{\gamma} + \eta_a) - \log(1 + \exp(Z_i\hat{\gamma} + \eta_a))$$

with scores $Z_i\hat{\gamma}$ given by first-stage estimation, provides estimates for η_a and for the corresponding standard errors.

The wage equation is estimated by panel OLS, assuming that there is no correlation between errors of the employment and the wage equations, a strong and probably invalid assumption. Point estimates of the β and the α's as well as estimates of the standard errors are obtained directly.

2.4 Support issues

In practice, there are potentially two kinds of support issues that have to be dealt with. First, some sampling units are likely to contain individuals from one population only. Because population D may be rare compared to population F and sampling units may be of small size, this issue has practical relevance. Our model assumes that, for every individual in the sample, the impact of the neighborhoods of residence and the one of the other covariates are additively separable. This means that the estimation on the whole sample or on the sample restricted to sampling units where both groups are present should yield close estimates. Moreover, this means that there is no way to recover the η_a's corresponding to sampling units in which there are only individuals belonging to population D, if the estimation has been made on population F. Therefore, for simplicity, the decomposition presented hereafter are done on the sample restricted to mixed sampling units (*i.e.* sampling units in which both groups are present), defined as:

$$\mathcal{A}_{D,F} = \{a | \exists (i, i') \in D \times F, a_i = a_{i'} = a\}$$

The choice of the estimation method also matters for the presentation of the decomposition. Obviously, whatever the method, only the sampling units for which there is a within-a variation of the E_{ia} contribute to the estimation of γ. Then, if the model is linear, all the η_a's, whether the sampling unit contributed to the estimation of γ or not, may be estimated. Conversely, if the model is not linear, only the η_a's corresponding to sampling units in which there is within variation of the explained variable may be estimated. Therefore, in the decomposition of a non-linear model, there will be two supplementary terms, named "support gaps for population j", that are equal to:

$$\frac{\sum_{i\in F} E_i}{Card(F)} - \frac{\sum_{i\in F|a_i\in\mathcal{A}_{D,F}} E_i}{Card(\{i\in F|a_i\in\mathcal{A}_{D,F}\})}, \text{ for population } F$$
$$\frac{\sum_{i\in D|a_i\in\mathcal{A}_{D,F}} E_i}{Card(\{i\in D|a_i\in\mathcal{A}_{D,F}\})} - \frac{\sum_{i\in D} E_i}{Card(D)}, \text{ for population } D$$

and which are just the differentials in means between the whole sample and the sample restricted to mixed sampling units.

2.5 Bias issues

When the equation of interest is assumed to be linear and that panel OLS is used to estimate its coefficients, both $\hat{\gamma}$ and $\hat{\eta}_a$ converge consistently to their true values. When the equation of employment is assumed to be non-linear and that conditional logit is used for the estimation, $\hat{g}amma$ converges to its true value, but $\hat{\eta}_a$ does not. There is an incidental parameter bias, first noted by Neyman & Scott (1948), that occurs when the number of sampling units grows large while the number of individuals per unit remains fixed.[9] Since Heckman (1981), simulations have proved the extent of the bias concerning the coefficients as well as the cluster effects in the panel data probit model. However, numerical studies by Greene (2004), Hahn & Newey (2004) and Fernandez-Val (2009) show that the problem is less severe when the quantities of interest are not the cluster effects themselves but the marginal effects. These studies found that, especially in the case of the static panel probit model, marginal effects suffer from relatively small biases.

Both a linear probability model and a logit model will be fitted for the employment. If the results of the two methods are qualitatively different, the bias issue cannot be avoided and some correction has to be done. Conversely, if both methods lead to similar results, one may be confident about the fact that incidental parameter biases may, in this case, be neglected.

3 Data

Before 2005, Labor Force Surveys undertaken by the Institut National de Statistiques et d'Etudes Economiques (Insee, Paris) did not provide information on the national origin of the parents of the surveyed persons. In 2003, the Formation and Qualification Professionnelle (FQP) survey (Insee, Paris) was the first major survey to collect such information on a representative sample of the French population. The precise question "What is the citizenship at birth of your mother/father?", together with the individual's nationality at birth and country of birth, is the key to identify the children of immigrants from a given country. Since 2005, the same set of questions are included in the Labor Force Survey, providing researchers with a larger sample.

3.1 The Labor Force Survey

Since July 2001, the LFS takes place quarterly and each household is interviewed six times. The first and the last interviews are done face-to-face whereas the second to the fifth are done by phone. One sixth of the sample is changed quarterly (so that two thirds are changed yearly). All individuals living in a sampled household and aged more than 15 are interviewed. About 70,000 individuals (in 45,000 households) are selected in the sample: the theoretical sample rate is around 1/600. The

[9] A review of this literature is proposed in Lancaster (2000).

realized sample rate (once non-answering individuals and non-consistent answers have been removed) is around 1/700.

The sampling frame, though complex, offers a nice way to control for very local effects. Households are not selected by simple random sampling or stratified sampling. The frame used is a three-fold geographical cluster sampling. First, using information from the 1999 Census, *primary sample units* (with several thousands inhabitants) are selected by stratified sampling. Then, within each of these primary units, at least one *sector*, consisting of between 120 and 240 contiguous households, is defined. Last, six *areas* of, on average, 20 contiguous households are constituted within each sector. Households of one given area are all interviewed simultaneously, they enter and leave the sample during the same quarter. After their last interview, they are replaced by households of another area belonging to the same sector. Because there are six areas in each sector, and because each area is interviewed six times, the current sample will be used for nine years and a new sample will have to have to be drawn in 2010, using fresher Census data.

The area level, made of about 20 contiguous households, is useful to control for very local neighborhood effects. Some local characteristics affecting one household in a given area will undoubtedly affect the other households of the same area. The same is true for the sector level, but to a lesser extent, as it may be made of a much larger number of households. Note also that, by the definition of primary sample units, the boundaries of areas or sectors cannot intersect those of administrative units (municipalities...). All inhabitants of given area or sector are thus subject to the same public goods offer. More details about the number of inhabitants of these geographic objects are given in the descriptive statistics section.

In this study, the quarterly Labor Force Surveys from 2005 to 2008 are used, restricted to the first interrogations of each individual. Note that geographical location of areas or sectors were not made available for this study: only anonymized IDs of areas and sectors were delivered. This allows to gather individuals living in the same sample unit. However, it is not possible to know precisely where the area or the sector is located and thus to add contextual variables to the analysis.

3.2 Sample and groups considered for the analysis

3.2.1 Scope of the study

Given the issues tackled by this paper, we start by reducing our sample. First, since we are interested in the employment status, we exclude students or retirees from our sample. Then, we keep only observations for which diplomas and ages are observed.

3.2.2 Variables considered for the analysis

Our variables of interest are the employment status of the individual and, if employed, her wage (or more precisely the logarithm of her wage). We work here with the most reliable wage variable that is available in the LFS, that represents current monthly earnings.

We create twelve dummies to characterize the type of household the individual belong to, crossing gender, presence of children, marital status and the employment status of her spouse. When relevant, the wage of the spouse was crossed with these dummies, leading to the creation of four more variables. We also consider age or potential experience (which is equal to the actual age less the age at the end of initial formation).[10] Education is taken into account by the inclusion of fifteen dummies for diploma, from no-diploma to master degree or more.

3.2.3 Sub-populations of interest

In order to interpret our results, we need our populations to be as close as possible, conditional on observable characteristics. There are at least two obvious reasons why comparisons are difficult between French workers and foreign migrants working in France. First, doubt may be cast on the fact that education or labor experience acquired in France or abroad are granted the same value by French employers. Then, the ability to speak French language may also explain some differences.

In this study, the focus is on individuals with French nationality, born in France or arrived in France before five years old, so that part of the preceding critics are addressed. Our reference group is composed by individuals whose both parents are born French in France. We build a group of interest composed by French individuals with at least one parent born with the citizenship of an African country.[11]

Table 1 presents some summary statistics on the two subpopulations: the reference group in the first two columns, the group of interest in the last ones. Columns 2 and 3 present summary statistics on the two groups, restricted on the areas where both groups are represented.[12] These may be compared to columns 1 and 4 where summary statistics for the whole populations are reported.

Columns 1 and 2 really differ from 3 and 4 over several aspects. First, individuals with African origin are younger (12 years of potential experience vs. about 19), they are more likely to have children (53% vs. 43%), they are less likely to reach the highest diploma and more likely to have no diploma at all. Differences in residence location are also striking. They are about five times as likely to live in ZUS, especially ZUS located within the Paris region. They also live twice more often in the Paris region (29% vs. 14%). On the labor market, they are less often on jobs (58% vs. 75%) and earn around 15% less monthly. Regarding their socio-professional status, they are less likely to be executive or professional (7% vs. 14%) or to occupy technical or educational occupations (16% vs. 22%) and more likely to be inactive that never worked (11% vs. 4%).

Restricting to the areas where more than one community lives does not change much the sample of the group of interest: about 155 persons are removed. On the contrary, the reference group is reduced to a third of its initial population. However, apart from variables relating to residence location, summary statistics do not seem much affected by this restriction.

3.3 Sampling units: areas and sectors

Figure 1 displays the distribution of the number of individuals in the sampling units – areas or sectors. When all individuals are considered, whether they belong to the group of interest or to the reference group, 376 areas contain only one individual and 292 areas contain only two. The median size is 15

[10] Potential experience is a better proxy for working experience for workers that hardly ever stopped working, than for those who stopped for longer periods (this is the case for women with maternity leaves), or that experienced longer and more frequent unemployment spells. In particular, if an individual is discriminated against in hirings, he will stay longer out of the employment. Therefore, a measurement error bias may arise for these groups. However, one should also admit that using exact working experience (which not available in the dataset anyway) is not less problematic, because of its potential endogeneity.

[11] We exclude individuals not declaring the nationality of both parents.

[12] The set of areas where both groups are represented is called the *mixed areas* in what follows.

individuals, the average size is 15.5 and the maximum size is 95. 5 sectors contain one individual and only 1 contains two. The median size of a sector is 47 individuals, their average size is 48.4 and the maximum size is 146. When only the individuals with French parents are considered, the distribution is roughly the same, as it is the largest group.

When only the individuals with African parents are considered, the situation is rather different. Nearly 80% of the areas (1830 over 2337) where they are present contain only one individual with African parents and 85% of these areas contain one or two individuals with African parents. The area where the individuals with African parents are the most numerous contain 21 of them. The situation is about the same with the sectors.

Figure 2 presents the average employment probability and the average wage in the areas and sectors conditional on their size.[13] The top graphs clearly displays an upward trend, meaning that larger areas and sectors contain individuals that are more often in employment. This may easily be explained by the fact that smaller areas and smaller sectors are more likely to be located in rural zones, where employment probability is lower. Moreover, variance clearly increases with the sampling unit size, reflecting the fact that larger units are less frequent. No clear trend appears for wages, but the increase in variance remains present.

This trend in employment suggests that sampling units of different sizes are likely to be different both in terms of observable and unobservable characteristics. Estimating our models with fixed-effects involves to leave out observations for which there is only one individual by cluster. This means that, for instance, it may be not possible to include fixed effects in a model over the population of individuals with African parents, as it would lead to exclude more than two thirds of the areas where they are living. In what follows, we will focus on estimations realized on the reference group, both to avoid this potential bias and to achieve more precise estimations.

4 Results

4.1 Estimation results

The employment equation is estimated alternatively by a conditional logit[14] and, assuming a linear model of probability, by panel OLS [15]. The wage equation is estimated by panel OLS. Two specifications have been tried: including cluster effects at the level of areas and at the level of sectors.

All estimations are realized on the population of the French individuals with French parents. Estimation results are presented in table 2, 3, 4 and 5. Table 2 presents results of conditional logits both on the whole sample and on the sample restricted to the mixed areas. Table 3 presents results of conditional logits when area- or sector-level cluster effects are introduced in the model. Table 4 compares results of conditional logits with area-level cluster effects with those obtained by logit, with no control for cluster effects.

Living in couple and having children are factors correlated with more employment for men and less employment for women. For both gender, being in couple with someone in employment is associated

[13]Smoothed conditional densities have been estimated using the `ksmooth` function in `R`; see R Development Core Team (2007).

[14]E. Kyriazidou provides, on her website, a script for estimating such models in Gauss, with unbalanced data. It is been translated to R and modified to make it able to handle data with large T. In particular, the gradient and the hessian matrix are computed analytically. What also improves the estimation of the standard errors of the coefficients.

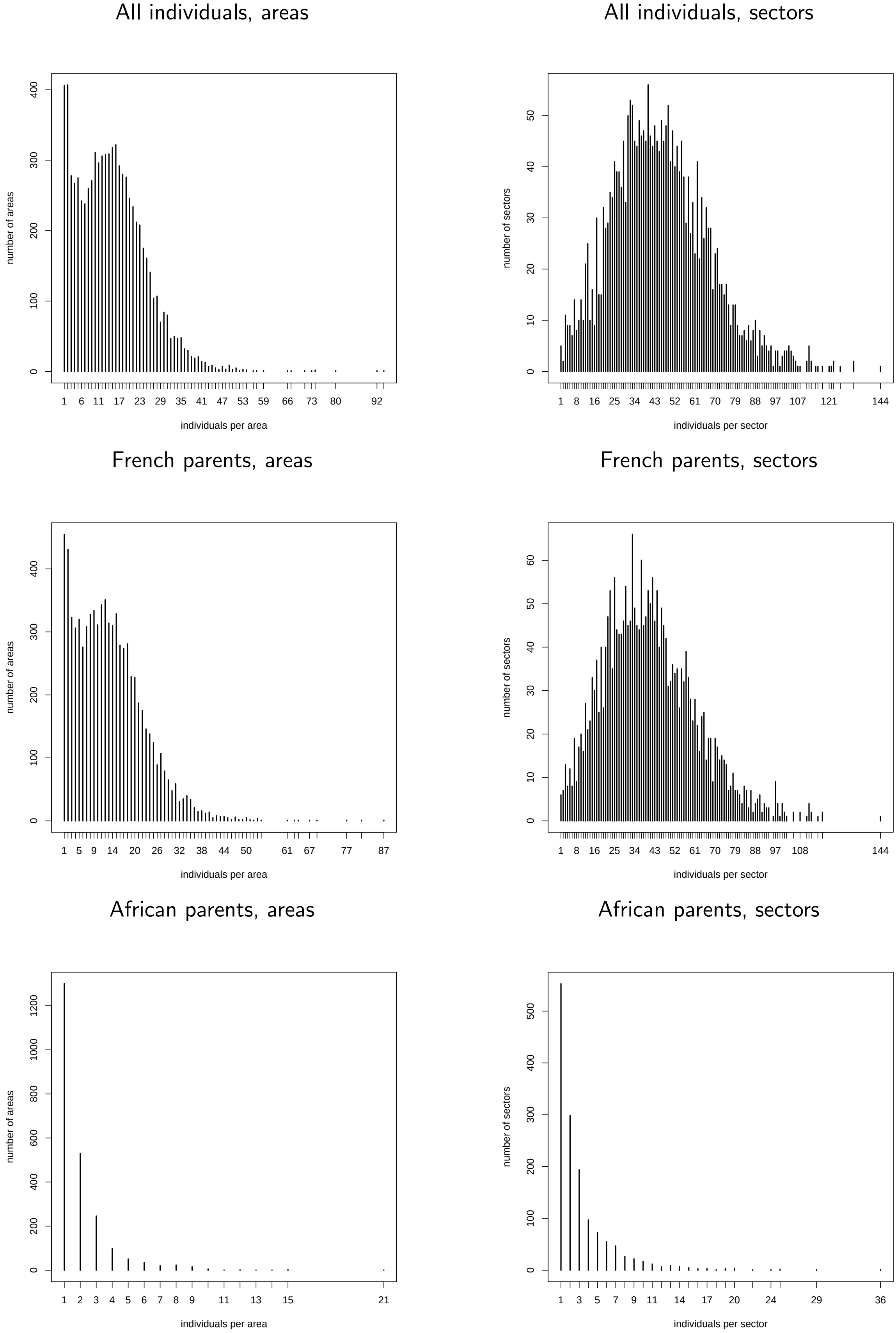
[15]To estimate panel OLS models, the R package plm has been used, see Croissant & Millo (2007).

Table 1: Summary Statistics

Variables	Populations			
	2 French parents whole sample	2 French parents mixed areas	African parents mixed areas	African parents whole sample
Socio-demographic				
Women	0.54	0.54	0.55	0.55
Couple	0.76	0.71	0.69	0.69
Children	0.43	0.42	0.53	0.53
Diploma				
Master and over	0.04	0.04	0.03	0.03
Ecole: Bac+3 and over	0.03	0.03	0.02	0.02
Univ.: Bac+4	0.04	0.04	0.03	0.03
Univ.: Bac+3	0.03	0.03	0.03	0.03
Univ.: Bac+2	0.02	0.02	0.01	0.01
Tech.: Bac+2	0.09	0.09	0.08	0.08
Health: Bac+2	0.03	0.02	0.01	0.01
Bac: General	0.08	0.08	0.08	0.08
Bac: Technical	0.05	0.05	0.05	0.05
Bac: Vocational	0.05	0.05	0.05	0.05
Bac-2: Vocational	0.26	0.25	0.22	0.22
Lower Sec. Educ. Deg.	0.09	0.09	0.10	0.10
No diploma	0.19	0.21	0.28	0.28
Residence				
Outside Paris region outside ZUS	0.82	0.70	0.54	0.54
Inside Paris region outside ZUS	0.13	0.18	0.22	0.22
ZUS outside Paris region	0.05	0.09	0.17	0.17
ZUS inside Paris region	0.01	0.03	0.07	0.07
Labor Market				
Employed	0.75	0.74	0.58	0.58
Full-time when employed	0.83	0.84	0.83	0.83
Potential experience (years)	18.92	17.86	12.50	12.49
Average monthly wage (euros)	1651.72	1622.80	1421.68	1421.05
Executive, Professional	0.14	0.13	0.07	0.07
Technical, Education	0.22	0.21	0.16	0.16
Clerical, Sales, Service Worker	0.28	0.29	0.29	0.29
Factory Operator	0.21	0.20	0.23	0.23
Inactive that worked before	0.12	0.12	0.14	0.14
Other inactive	0.04	0.04	0.11	0.11
Misceallanous				
Average Nobs per sample area	16.20	16.80	13.22	13.11
Nobs	102830	33052	4578	4623

Source: Labor Force Survey 2005-2008 (Insee).
Reading note: 82% of individuals with French parents live outside Paris region and outside a ZUS. 70% of individuals who live in areas with at least one individual with African parents and with French parents live outside Paris region and outside a ZUS.

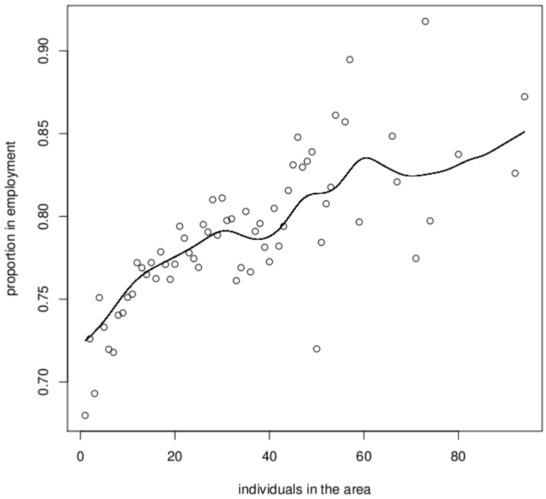
Figure 1: Areas and Sectors: size distribution of sampling units, by population



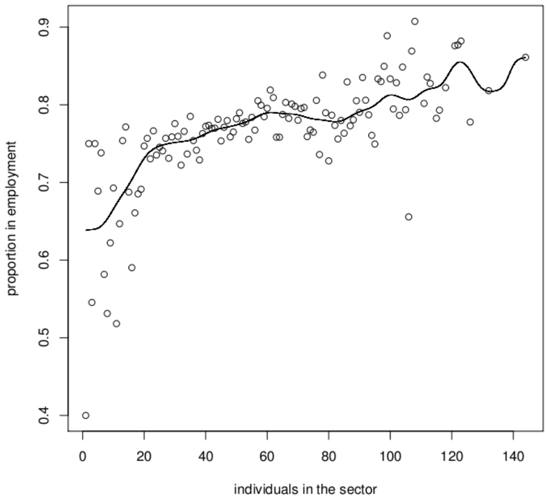
Source: Labor Force Survey 2005-2008 (Insee).
Reading note: Considering all individuals in the sample, there are more than 400 sampling units with 2 individuals.

Figure 2: Wage and employment probability means, by sampling unit size

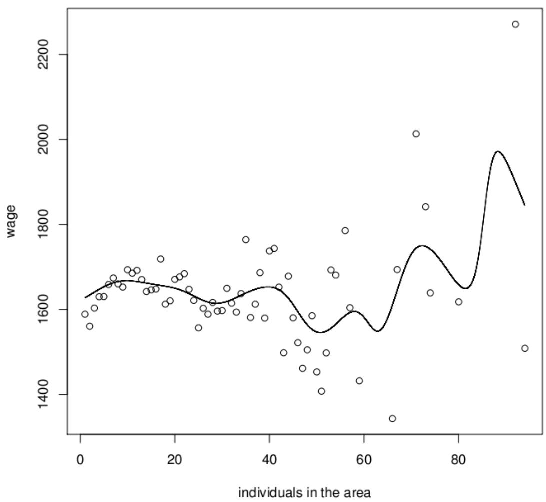
Employment probability, areas



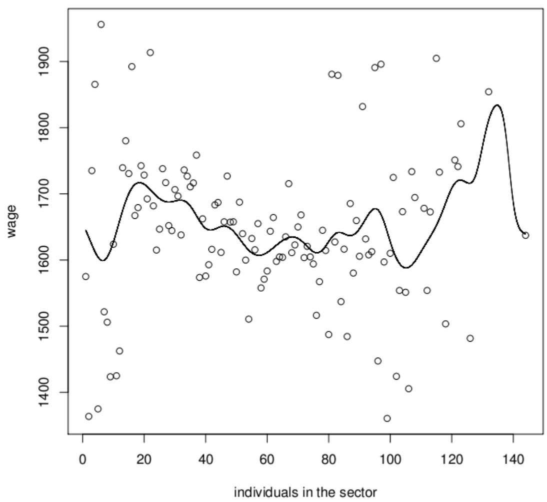
Employment probability, sectors



Wage, areas



Wage, sectors



Source: Labor Force Survey 2005-2008 (Insee).
Note: Smoothed conditional density of employment/wage with respect to the sampling unit size, usinf the Gaussian kernel.

with more chance to be employed. Finally, women tend to earn lower wages, everything else equal. Coefficients relating to potential experience have the usual signs: experience has an increasing yet concave role on the probability to be employed as well as on wages. Degrees higher than Bac+3 as well technical, health-oriented Bac+2 and technical and vocational Bac are significantly more helpful to find a job than a General Bac. Only the Lower Secondary Education Degree and no degree are significantly less favorable than the General Bac. Education, seniority and working time also have expected effects on wages.

As described in the methodological section, we infer cluster effects of the employment equation by MLE. Figure 3 displays the smoothed densities of cluster effects for the two subpopulations. The distribution relating to the group of interest displays more variance and is shifted to the left, especially in the lower half of the distribution. The modes of the two distributions are about the same. This shows that individuals with African origin tend to live in areas slighly less favorable in terms of access to employment.

The distributions of the cluster effects of the wage equation across the two populations are not reported: the two distributions are almost the same.

4.2 Decompositions

In this section, we present the results of the decomposition based on the estimation of the employment and the wage equations, with or without including cluster effects in the equations. Results are reported in table 6.

The component relating to differentials in cluster effects accounts for about 25% of the employment gap, while differences in individual characteristics account for only 5%. Two thirds of the 15 points of employment differential remain unexplained. Compared to benchmark decompositions based on estimations in which cluster effects are excluded, the inclusion of cluster effects in the model do curb the unexplained part, yet to a modest extent.[16] The wage story is quite different: whether cluster effects are included or not in the model, the unexplained gap of the wage differential remains virtually zero. While the differences in group's average characteristics entirely account for the wage gap in the no-cluster-effects model, the differential in the quality of the neighborhoods seems to account for 25% of the gap when cluster effects are included.

4.3 Robustness and specification issues

Our model assumes that location adds a constant, positive or negative, to the individual propensity to be employment or to the individual log-wage. This may be interpreted in terms of changing the level of the unobservable component of the employment or the wage. If location changes also, say, returns to observable skills, our model is likely to be subject to some specification error. Columns (3) and (4) of table 2 reports estimation results for the population of individuals with French parents, no matter the area they live in. There are very few differences on the signs or the values of the estimates. Some coefficients, like those relating to spouse wages for women or to the Technical Bac, become significant, which is understandable as switching from mixed sampling units to every sampling units triples the sample size. The fact the coefficient do not differ in the two samples is consistent with our assumption of additive separability between neighborhood and covariates effects.

[16]Note that standard errors are only given here for decomposition stemming from panel OLS estimations. They are obtained by bootstrap on the observations. Bootstrap on the conditional logit estimation has still to be performed, but computations are quite heavy.

Table 2: Estimates of the employment equation parameters on the population of individuals with French parents, with area-level cluster effects

Covariates	Mixed areas		All areas	
	Cond. Log FE	Panel OLS	Cond. Log FE	Panel OLS
Intercept	–	–	–	–
Family Situation				
Single women with children	-0.75^{***} (0.07)	-0.13^{***} (0.01)	-0.75^{***} (0.04)	-0.13^{***} (0.01)
Men with working spouse with children	0.81^{***} (0.10)	0.08^{***} (0.01)	0.88^{***} (0.06)	0.08^{***} (0.01)
Men with working spouse without children	0.64^{***} (0.09)	0.09^{***} (0.01)	0.82^{***} (0.05)	0.11^{***} (0.01)
Men with non-working spouse with children	0.32^{***} (0.06)	0.04^{***} (0.01)	0.37^{***} (0.04)	0.04^{***} (0.01)
Men with non-working spouse without children	-0.05 (0.05)	-0.01 (0.01)	-0.03 (0.03)	-0.00 (0.00)
Women with working spouse with children	-0.86^{***} (0.07)	-0.15^{***} (0.01)	-0.79^{***} (0.04)	-0.13^{***} (0.01)
Women with working spouse without children	0.04 (0.08)	0.01 (0.01)	0.01 (0.04)	0.01 (0.01)
Women with non-working spouse with children	-0.98^{***} (0.06)	-0.17^{***} (0.01)	-0.97^{***} (0.03)	-0.17^{***} (0.01)
Women with non-working spouse without children	-0.61^{***} (0.05)	-0.11^{***} (0.01)	-0.61^{***} (0.03)	-0.11^{***} (0.00)
*Spouse wage*Men with working spouse with children*	-0.13 (0.17)	-0.04^{*} (0.02)	0.01 (0.09)	-0.02^{**} (0.01)
*Spouse wage*Men with working spouse without children*	-0.16 (0.15)	-0.04^{**} (0.02)	-0.11 (0.08)	-0.03^{***} (0.01)
*Spouse wage*Women with working spouse with children*	-0.07 (0.11)	0.01 (0.02)	-0.19^{***} (0.06)	-0.02 (0.01)
*Spouse wage*Women with working spouse without children*	-0.08 (0.14)	-0.01 (0.02)	-0.17^{**} (0.07)	-0.03^{***} (0.01)
Experience in Labor Force	0.08^{***} (0.00)	0.01^{***} (0.00)	0.09^{***} (0.00)	0.02^{***} (0.00)
Experience Squared/100	-0.22^{***} (0.01)	-0.04^{***} (0.00)	-0.24^{***} (0.01)	-0.04^{***} (0.00)
Diploma Level				
Bac: General	–	–	–	–
Master and over	0.46^{***} (0.10)	0.07^{***} (0.01)	0.60^{***} (0.06)	0.08^{***} (0.01)
Ecoles: Bac+3 and over	0.40^{***} (0.11)	0.05^{***} (0.02)	0.41^{***} (0.06)	0.05^{***} (0.01)
Univ: Bac+4	0.46^{***} (0.10)	0.07^{***} (0.01)	0.63^{***} (0.06)	0.09^{***} (0.01)
Univ: Bac+3	0.66^{***} (0.11)	0.09^{***} (0.02)	0.56^{***} (0.06)	0.08^{***} (0.01)
Univ: Bac+2	0.37^{***} (0.13)	0.05^{**} (0.02)	0.25^{***} (0.07)	0.03^{***} (0.01)
Tech: Bac+2	0.37^{***} (0.08)	0.05^{***} (0.01)	0.37^{***} (0.04)	0.05^{***} (0.01)
Health: Bac+2	0.88^{***} (0.13)	0.12^{***} (0.02)	0.94^{***} (0.07)	0.13^{***} (0.01)
Bac: Technical	0.13 (0.09)	0.02 (0.01)	0.11^{**} (0.05)	0.02^{**} (0.01)
Bac: Vocational	0.23^{***} (0.09)	0.03^{**} (0.01)	0.20^{***} (0.05)	0.03^{***} (0.01)
Bac-2: Vocational	-0.26^{***} (0.06)	-0.04^{***} (0.01)	-0.13^{***} (0.03)	-0.02^{***} (0.01)
Lower Sec. Educ. Deg.	-0.46^{***} (0.07)	-0.08^{***} (0.01)	-0.32^{***} (0.04)	-0.05^{***} (0.01)
No diploma	-0.86^{***} (0.06)	-0.16^{***} (0.01)	-0.71^{***} (0.04)	-0.13^{***} (0.01)
Quarter dummies	*Yes*	*Yes*	*Yes*	*Yes*
Nobs	31409	33001	97232	102375

Source: Labor Force Survey 2005-2008 (Insee).
Notes: 1 star means 90%-significant, 2 stars means 95%-significant and 3 stars means 99%-significant. Standard errors are in parentheses. The first two columns display estimations run on the sample of individuals with French parents living in areas where at least one individual with African parents lives. The last two columns are run on the whole sample. Columns 1 and 3 are obtained by conditional logits. Columns 2 and 4 are obtained by panel OLS.

Table 3: Estimates of the employment equation parameters on the population of individuals with French parents, with area-level or sector-level cluster effects

Covariates	Area-level FE		Sector-level FE	
	Mixed areas	All areas	Mixed sectors	All sectors
Intercept	–	–	–	–
Family Situation				
Single women with children	-0.75^{***} (0.07)	-0.75^{***} (0.04)	-0.77^{***} (0.07)	-0.81^{***} (0.04)
Men with working spouse with children	0.81^{***} (0.10)	0.88^{***} (0.06)	0.94^{***} (0.10)	1.09^{***} (0.06)
Men with working spouse without children	0.64^{***} (0.09)	0.82^{***} (0.05)	0.72^{***} (0.09)	0.99^{***} (0.05)
Men with non-working spouse with children	0.32^{***} (0.06)	0.37^{***} (0.04)	0.32^{***} (0.06)	0.34^{***} (0.03)
Men with non-working spouse without children	-0.05 (0.05)	-0.03 (0.03)	-0.03 (0.05)	-0.04 (0.03)
Women with working spouse with children	-0.86^{***} (0.07)	-0.79^{***} (0.04)	-0.80^{***} (0.07)	-0.74^{***} (0.04)
Women with working spouse without children	0.04 (0.08)	0.01 (0.04)	0.13^{*} (0.08)	0.14^{***} (0.04)
Women with non-working spouse with children	-0.98^{***} (0.06)	-0.97^{***} (0.03)	-0.98^{***} (0.05)	-1.00^{***} (0.03)
Women with non-working spouse without children	-0.61^{***} (0.05)	-0.61^{***} (0.03)	-0.60^{***} (0.05)	-0.64^{***} (0.03)
*Spouse wage*Men with working spouse with children*	-0.13 (0.17)	0.01 (0.09)	-0.12 (0.17)	0.02 (0.09)
*Spouse wage*Men with working spouse without children*	-0.16 (0.15)	-0.11 (0.08)	-0.19 (0.15)	-0.16^{*} (0.08)
*Spouse wage*Women with working spouse with children*	-0.07 (0.11)	-0.19^{***} (0.06)	-0.07 (0.11)	-0.20^{***} (0.06)
*Spouse wage*Women with working spouse without children*	-0.08 (0.14)	-0.17^{**} (0.07)	-0.10 (0.14)	-0.25^{***} (0.07)
Experience in Labor Force	0.08^{***} (0.00)	0.09^{***} (0.00)	0.08^{***} (0.00)	0.09^{***} (0.00)
Experience Squared/100	-0.22^{***} (0.01)	-0.24^{***} (0.01)	-0.22^{***} (0.01)	-0.25^{***} (0.01)
Diploma Level				
Bac: General	–	–	–	–
Master and over	0.46^{***} (0.10)	0.60^{***} (0.06)	0.46^{***} (0.10)	0.60^{***} (0.06)
Ecoles: Bac+3 and over	0.40^{***} (0.11)	0.41^{***} (0.06)	0.40^{***} (0.11)	0.43^{***} (0.06)
Univ: Bac+4	0.46^{***} (0.10)	0.63^{***} (0.06)	0.49^{***} (0.10)	0.67^{***} (0.06)
Univ: Bac+3	0.66^{***} (0.11)	0.56^{***} (0.06)	0.68^{***} (0.11)	0.62^{***} (0.06)
Univ: Bac+2	0.37^{***} (0.13)	0.25^{***} (0.07)	0.36^{***} (0.13)	0.23^{***} (0.07)
Tech: Bac+2	0.37^{***} (0.08)	0.37^{***} (0.04)	0.38^{***} (0.08)	0.39^{***} (0.04)
Health: Bac+2	0.88^{***} (0.13)	0.94^{***} (0.07)	0.93^{***} (0.13)	1.06^{***} (0.07)
Bac: Technical	0.13 (0.09)	0.11^{**} (0.05)	0.15^{*} (0.09)	0.15^{***} (0.05)
Bac: Vocational	0.23^{***} (0.09)	0.20^{***} (0.05)	0.24^{***} (0.09)	0.22^{***} (0.05)
Bac-2: Vocational	-0.26^{***} (0.06)	-0.13^{***} (0.03)	-0.26^{***} (0.06)	-0.12^{***} (0.03)
Lower Sec. Educ. Deg.	-0.46^{***} (0.07)	-0.32^{***} (0.04)	-0.45^{***} (0.07)	-0.31^{***} (0.04)
No diploma	-0.86^{***} (0.06)	-0.71^{***} (0.04)	-0.91^{***} (0.06)	-0.72^{***} (0.04)
Quarter dummies	Yes	Yes	Yes	Yes
Nobs	31409	97232	32234	102550

Source: Labor Force Survey 2005-2008 (Insee).
Notes: 1 star means 90%-significant, 2 stars means 95%-significant and 3 stars means 99%-significant. Standard errors are in parentheses. The first two columns display estimations controlling for area-level cluster effects. The last two columns display estimations controlling for sector-level cluster effects. Column 1 displays estimates on the sample of individuals with French parents living in areas where at least one individual with African parents lives. Column 3 displays estimates on the sample of individuals with French parents living in sectors where at least one individual with African parents lives. Estimates reported in columns 2 and 4 are run on the whole sample. All estimates are obtained by conditional logits.

Table 4: Estimates of the employment equation parameters on the population of individuals with French parents, with and without area-level cluster effects

Covariates	Area-level FE		Logit	
	Mixed areas	All areas	Mixed areas	All areas
Intercept	–	–	–	–
Family Situation				
Single women with children	-0.75^{***} (0.07)	-0.75^{***} (0.04)	-0.78^{***} (0.06)	-0.76^{***} (0.04)
Men with working spouse with children	0.81^{***} (0.10)	0.88^{***} (0.06)	1.21^{***} (0.10)	1.29^{***} (0.06)
Men with working spouse without children	0.64^{***} (0.09)	0.82^{***} (0.05)	1.00^{***} (0.09)	1.18^{***} (0.05)
Men with non-working spouse with children	0.32^{***} (0.06)	0.37^{***} (0.04)	0.34^{***} (0.05)	0.38^{***} (0.03)
Men with non-working spouse without children	-0.05 (0.05)	-0.03 (0.03)	0.05 (0.05)	0.05^{*} (0.03)
Women with working spouse with children	-0.86^{***} (0.07)	-0.79^{***} (0.04)	-0.51^{***} (0.06)	-0.45^{***} (0.03)
Women with working spouse without children	0.04 (0.08)	0.01 (0.04)	0.39^{***} (0.07)	0.34^{***} (0.04)
Women with non-working spouse with children	-0.98^{***} (0.06)	-0.97^{***} (0.03)	-0.84^{***} (0.05)	-0.85^{***} (0.03)
Women with non-working spouse without children	-0.61^{***} (0.05)	-0.61^{***} (0.03)	-0.46^{***} (0.04)	-0.49^{***} (0.03)
*Spouse wage*Men with working spouse with children*	-0.13 (0.17)	0.01 (0.09)	-0.03 (0.16)	0.05 (0.09)
*Spouse wage*Men with working spouse without children*	-0.16 (0.15)	-0.11 (0.08)	-0.08 (0.14)	-0.01 (0.08)
*Spouse wage*Women with working spouse with children*	-0.07 (0.11)	-0.19^{***} (0.06)	-0.01 (0.11)	-0.15^{**} (0.06)
*Spouse wage*Women with working spouse without children*	-0.08 (0.14)	-0.17^{**} (0.07)	0.00 (0.13)	-0.16^{**} (0.07)
Experience in Labor Force	0.08^{***} (0.00)	0.09^{***} (0.00)	0.09^{***} (0.00)	0.09^{***} (0.00)
Experience Squared/100	-0.22^{***} (0.01)	-0.24^{***} (0.01)	-0.21^{***} (0.01)	-0.23^{***} (0.01)
Diploma Level				
Bac: General	–	–	–	–
Master and over	0.46^{***} (0.10)	0.60^{***} (0.06)	0.42^{***} (0.09)	0.56^{***} (0.05)
Ecoles: Bac+3 and over	0.40^{***} (0.11)	0.41^{***} (0.06)	0.43^{***} (0.10)	0.39^{***} (0.06)
Univ: Bac+4	0.46^{***} (0.10)	0.63^{***} (0.06)	0.50^{***} (0.09)	0.62^{***} (0.05)
Univ: Bac+3	0.66^{***} (0.11)	0.56^{***} (0.06)	0.68^{***} (0.10)	0.55^{***} (0.06)
Univ: Bac+2	0.37^{***} (0.13)	0.25^{***} (0.07)	0.35^{***} (0.12)	0.22^{***} (0.07)
Tech: Bac+2	0.37^{***} (0.08)	0.37^{***} (0.04)	0.46^{***} (0.07)	0.44^{***} (0.04)
Health: Bac+2	0.88^{***} (0.13)	0.94^{***} (0.07)	0.95^{***} (0.13)	0.96^{***} (0.07)
Bac: Technical	0.13 (0.09)	0.11^{**} (0.05)	0.20^{**} (0.08)	0.18^{***} (0.05)
Bac: Vocational	0.23^{***} (0.09)	0.20^{***} (0.05)	0.32^{***} (0.08)	0.24^{***} (0.04)
Bac-2: Vocational	-0.26^{***} (0.06)	-0.13^{***} (0.03)	-0.29^{***} (0.06)	-0.12^{***} (0.03)
Lower Sec. Educ. Deg.	-0.46^{***} (0.07)	-0.32^{***} (0.04)	-0.47^{***} (0.06)	-0.31^{***} (0.04)
No diploma	-0.86^{***} (0.06)	-0.71^{***} (0.04)	-1.02^{***} (0.06)	-0.79^{***} (0.03)
Quarter dummies	Yes	Yes	Yes	Yes
Nobs	31409	97232	33052	102830

Source: Labor Force Survey 2005-2008 (Insee).
Notes: 1 star means 90%-significant, 2 stars means 95%-significant and 3 stars means 99%-significant. Standard errors are in parentheses. The first two columns display estimations controlling for area-level cluster effects, obtained by conditional logit. The last two columns display logit estimations, not controlling for any cluster effect. Columns 1 and 3 displays estimates on the sample of individuals with French parents living in areas where at least one individual with African parents lives. Estimations reported in columns 2 and 4 are run on the whole sample.

Table 5: Estimates of the wage equation parameters on the population of individuals with French parents, with area-level or without cluster effects

Covariates	Panel OLS		OLS	
	Mixed areas	All areas	Mixed areas	All areas
Intercept	–	–	–	–
Working time				
Full-time	–	–	–	–
Less than 50%	-1.21^{***} (0.01)	-1.23^{***} (0.01)	-1.24^{***} (0.01)	-1.25^{***} (0.01)
50%	-0.67^{***} (0.01)	-0.69^{***} (0.01)	-0.67^{***} (0.01)	-0.69^{***} (0.01)
Between 50% and 80%	-0.50^{***} (0.01)	-0.50^{***} (0.01)	-0.53^{***} (0.01)	-0.51^{***} (0.01)
80%	-0.23^{***} (0.01)	-0.24^{***} (0.01)	-0.23^{***} (0.01)	-0.24^{***} (0.01)
More than 80%	-0.19^{***} (0.02)	-0.20^{***} (0.01)	-0.22^{***} (0.02)	-0.20^{***} (0.01)
Gender				
Men	–	–	–	–
Women	-0.18^{***} (0.00)	-0.19^{***} (0.00)	-0.18^{***} (0.00)	-0.18^{***} (0.00)
Experience in Labor Force	0.02^{***} (0.00)	0.02^{***} (0.00)	0.02^{***} (0.00)	0.02^{***} (0.00)
Experience Squared/100	-0.03^{***} (0.00)	-0.04^{***} (0.00)	-0.04^{***} (0.00)	-0.04^{***} (0.00)
Seniority				
Less than 1 year	–	–	–	–
1 to 5 years	0.09^{***} (0.01)	0.10^{***} (0.00)	0.10^{***} (0.01)	0.10^{***} (0.00)
5 to 10 years	0.16^{***} (0.01)	0.16^{***} (0.00)	0.16^{***} (0.01)	0.16^{***} (0.00)
More than 10 years	0.25^{***} (0.01)	0.26^{***} (0.00)	0.26^{***} (0.01)	0.26^{***} (0.00)
Diploma Level				
Bac: General	–	–	–	–
Master and over	0.41^{***} (0.01)	0.44^{***} (0.01)	0.45^{***} (0.01)	0.49^{***} (0.01)
Ecoles: Bac+3 and over	0.49^{***} (0.01)	0.49^{***} (0.01)	0.55^{***} (0.01)	0.56^{***} (0.01)
Univ: Bac+4	0.14^{***} (0.01)	0.15^{***} (0.01)	0.12^{***} (0.01)	0.14^{***} (0.01)
Univ: Bac+3	0.27^{***} (0.01)	0.26^{***} (0.01)	0.29^{***} (0.01)	0.27^{***} (0.01)
Univ: Bac+2	0.05^{***} (0.02)	0.07^{***} (0.01)	0.04^{**} (0.02)	0.07^{***} (0.01)
Tech: Bac+2	0.12^{***} (0.01)	0.12^{***} (0.01)	0.11^{***} (0.01)	0.11^{***} (0.01)
Health: Bac+2	0.26^{***} (0.02)	0.24^{***} (0.01)	0.24^{***} (0.02)	0.22^{***} (0.01)
Bac: Technical	-0.04^{***} (0.01)	-0.04^{***} (0.01)	-0.07^{***} (0.01)	-0.06^{***} (0.01)
Bac: Vocational	-0.02^{*} (0.01)	-0.03^{***} (0.01)	-0.06^{***} (0.01)	-0.06^{***} (0.01)
Bac-2: Vocational	-0.15^{***} (0.01)	-0.17^{***} (0.01)	-0.20^{***} (0.01)	-0.21^{***} (0.01)
Lower Sec. Educ. Deg.	-0.13^{***} (0.01)	-0.15^{***} (0.01)	-0.17^{***} (0.01)	-0.18^{***} (0.01)
No diploma	-0.28^{***} (0.01)	-0.30^{***} (0.01)	-0.34^{***} (0.01)	-0.36^{***} (0.01)
Quarter dummies	Yes	Yes	Yes	Yes
Nobs	22114	69891	24378	77447

Source: Labor Force Survey 2005-2008 (Insee).
Notes: 1 star means 90%-significant, 2 stars means 95%-significant and 3 stars means 99%-significant. Standard errors are in parentheses. Estimations are performed by panel OLS. The first column presents the estimates over the population of individuals with French parents living in areas where at least one individual with African parents lives. The second column presents the estimates over the whole sample.

Figure 3: Densities of cluster effects, by subpopulation

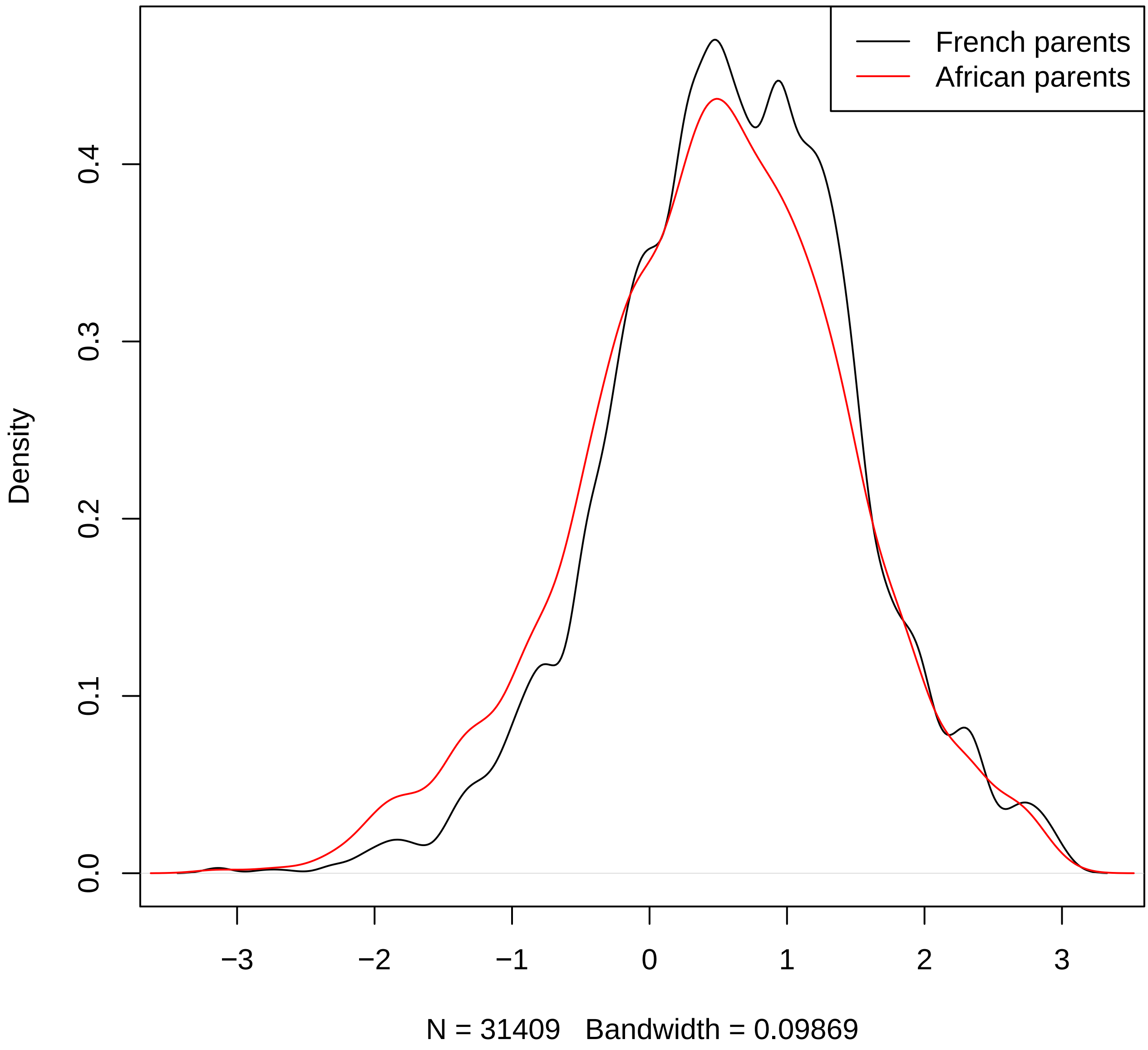


Table 6: Decomposition of the employment and the wage differentials

	With cluster effects			Without cluster effects	
	Employment		Wage	Employment	Wage
	Cond. logit	Panel OLS	Panel OLS	Logit	OLS
Raw gap	0.155	0.153 [0.139−0.166]	0.113 [0.095−0.132]	0.155	0.117
Support gap (reference pop.)	0.011	–	–	–	–
Area quality gap	0.042 [0.042−0.042]	0.038 [0.028−0.046]	0.026 [0.013−0.043]	–	–
Covariate gap	0.007 [0.006−0.012]	0.007 [0.002−0.011]	0.091 [0.074−0.106]	0.030	0.117
Unexplained	0.090 [0.085−0.091]	0.108 [0.094−0.124]	−0.005 [−0.020−0.009]	0.125	0.000
Support gap (pop. of interest)	0.005	–	–	–	–

Source: Labor Force Survey 2005-2008 (Insee).
Note: In brackets are reported 95% intervals of confidence, obtained by full bootstrap on the observations.

Table 3 present estimates for the employment equation, comparing regressions in which area-level cluster effects are introduced versus those with sector-level cluster effects. Differences between the estimates controlling for area- and sector-level clusters are small. The only qualitative difference is on the coefficient on women with working spouse without children. Table 4 compares the conditional logit with area-level cluster effects with the logit that takes no account of the clustering structure. In this case, differences are stronger but still quite small. Interestingly, the estimates of the sector-level cluster effects model seem to lie in between the two others, but closer to the area-level one.

Table 5 also displays some differences, yet small between results from panel OLS and OLS estimations.

As evoked in the Methodology section, the counterfactuals involved in the decomposition of the employment equation are likely to be biased when the model is estimated by conditional logit. First, this bias is documented to be small in several studies as far as marginal effects are concerned, see Greene (2004), Hahn & Newey (2004) and Fernandez-Val (2009). Second, as such a bias does not exist when the model is estimated and as the decompositions pbtained in the conditional logit and the linear cases are rather similar, it might be concluded that the incidental parameter is not a first-order issue here.

4.4 Discussion

These results are evidence that location matters for both employment probability and wage. However, the French case contrasts with other countries' situations in that segregation or spatial mismatch issues do not seem to be the main determinant to explain the differentials in labor market outcomes between individuals with French parents and individuals with African parents. For the wage, most of the gap is explained by differences in observable covariates while a quarter is accounted for by differences in neighborhood quality. None of the gap remains unexplained. For access to employment, on the other hand, differences are hardly explained by differences in characteristics or neighborhood quality. The differential in covariates accounts for about 5%, the one in the residence location for about 25%, while the remaining is unexplained.

Our estimations are realized without taking too much care of endogeneity issues. The identification of the impact of individual characteristics on wages is widely known to suffer from many endogeneity problems. Education may be correlated with some unobserved individual talent, firm seniority with some unobserved component of individual productivity... Is our analysis still valid despite of this issue? Obviously, potential endogeneity impedes the interpretation of the estimated coefficients in the employment and the wage equations as causal coefficients. They are the sum of the true causal coefficient and the impact of the unobserved characteristics correlated with the observed ones. Thus, the decomposition analysis remains sensible in spite of endogeneity if one assumes that the expectations of the unobservables relevant to wage or employment are the same in each group, conditional on observables.[17]

The coefficients of cluster-effects are also likely to be endogenous. Obviously, residence location is not an exogenous phenomenon, and people will choose their location according to their observed and unobserved characteristics. For instance, as tackled by Tiebout (1956) or in the bulk of literature exploring the mechanisms of social segregation, the *sorting* phenomenon predicts that individuals that are endowed with higher productivity (a part of which being potentially unobservable) tend to cluster. The spatial mismatch literature adds that they would cluster in areas that are located closer to jobs. Therefore, there might exist a positive correlation between unobserved factors of the employment (or the wage) equation and the cluster effects. That would bias upward the estimates of cluster effects obtained in this paper. The interpretation of the results have to include this issue. The component relating to the cluster effects sums up many factors: the impact of the neighborhood quality itself (through spatial mismatch or human capital externalities), the impact of redlining discrimination and the sorting phenomenon. If anything, the computed component is thus an upper bound of the contribution to employment and wage gaps of the differences in residence neighborhood quality. Conversely, the unexplained component is a lower bound of the unexplained component that would be obtained if redlining discrimination and sorting were accounted for in the estimation of the cluster effects. The unexplained component of the employment gap is therefore *at least* of 10 points.

Another issue that has not been dealt with is selection into employment, that may bias coefficients of the wage equation. A correlation between unobservables of the wage and the employment equations, a very likely case, induces a bias on the coefficients of the wage equation. In line with the former argument about endogeneity, this would not be a problem if the bias were symmetric across groups. In the selection case, this assumption seems quite unlikely. As is noticed in this analysis of the employment probability, there exists unexplained differences across groups, even after controlling for differences in observables. Thus, it seems very likely that selection processes differ across groups, and that the symmetry assumption does not hold. In practice, however, Aeberhardt et al. (2009) attempt to control for selection in the wage equation, in the case of ethnic differentials in France. Their estimations, that do not include cluster effects, show that decomposition results are not qualitatively changed.

The main drawback of the Blinder-Oaxaca decomposition is that there might exist unobserved individual characteristics correlated with the individual's origin but only partially correlated with observables. If such unobserved characteristics exist, it is impossible to identify the unexplained part of the gap as discrimination. In this study, the introduction of cluster effects in the employment equation reduces the unexplained component, but the latter remains the main component of the employment gap. This suggests that neighborhood differences accounts for around 25% of the unexplained component in

[17] To see this, imagine the following simple case in which the variable of interest E_i depends only on the observable scalar x_i and on the unobservable z_i, such that: $E_i = \alpha + \beta_x x_i + \beta_z z_i + \varepsilon$ and that $\mathbb{E}[z|x] = \mu$. Then, the estimated coefficient $\hat{\beta}_x$ relating to x will lead to $\mathbb{E}[\hat{\beta}_x] = \beta_x + \beta_z \mu$. For the decomposition to remain relevant, one needs μ to be equal across groups.

the employment decompositions based on estimations not controlling for cluster effects. This means that the other 75% of the unexplained component are uncorrelated both to observable characteristics and to the quality of the neighborhood of residence. What else may remain in the unexplained component of the employment gap? Discrimination is an obvious candidate. The ability to speak French language is sometimes claimed to be another one, see for instance Domingues Dos Santos & Wolff (2007).[18] The quality of networks is yet another possibility: children of migrants may be penalized the weaker quality of their parents' networks, with respect to individuals with French parents. This hypothesis could be tested comparing outcomes of children of migrants whose wave of arrival in France was simultanous, but whose country of origin differ.

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[18]One can think of two strategies to attempt to control for the influence of language. First, some surveys explicitly ask individuals about the language that was spoken at home during childhood but it is not the case in the French LFS. Then, one could try to compare outcomes between individuals coming from Martinique and Guadeloupe and others coming from African countries: the former often speaking French at home while the latter usually not doing.

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