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THE EFFECTS OF SEGREGATION AND SPATIAL MISMATCH ON UNEMPLOYMENT: EVIDENCE FROM FRANCE

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Abstract

In this paper, we investigate how residential segregation and bad physical access to jobs contribute to urban unemployment in the Paris region. We first survey the general mechanisms according to which residential segregation and spatial mismatch can have adverse labor-market outcomes. We then discuss the extent of the problem with the help of relevant descriptive statistics computed from the 1999 Census of the Population and from the 2000 General Transport Survey. Finally, we estimate the effect of indices of segregation computed at the neighborhood and municipality levels, as well as job accessibility indices on the labor-market transitions out of unemployment using the 1990-2002 Labor Force Survey. Our results show that neighborhood segregation is a key factor that prevents unemployed workers from finding a job. These results are robust to potential location endogeneity biases.

Key words: residential segregation, spatial mismatch, urban unemployment, sensitivity analysis.
JEL Classification: J64, R14.

Résumé

Ce travail étudie la façon dont la ségrégation résidentielle et la déconnexion physique aux lieux d'emploi contribue au chômage urbain en Ile-de-France Nous rappelons dans une revue de la littérature les mécanismes généraux selon lesquels la ségrégation résidentielle et le mauvais appariement spatial sont sources de difficultés sur le marché du travail. Nous présentons ensuite des statistiques descriptives pour illustrer ces questions en Ile-de-France à partir du Recensement de la Population de 1999 et de l'Enquête Globale des Transports en 2000. Enfin, nous estimons l'effet d'indices de ségrégation calculés à l'échelle du voisinage et de la commune et d'indices d'accessibilité aux emplois sur les transitions hors du chômage en utilisant les Enquêtes Emploi 1990-2002. Nos résultats montrent que la ségrégation résidentielle est un facteur clé qui empêche le retour à l'emploi des chômeurs. Ce résultat est robustes aux biais d'endogénéité de localisation.

Mots-clés: ségrégation résidentielle, spatial mismatch, chômage urbain, analyse de sensibilité.

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1 Introduction

In november 2005, an isolated act of police violence that occurred in a low-income neighborhood out of Paris triggered an unexpected wave of riots that quickly spread to many distressed areas across the country. Even though suburban riots had sporadically taken place over the past three decades, most observers were surprised by the renewed intensity of the phenomenon ($9,193$ cars were burnt over a three-week period) and, for the first time, by its generalization to more than 170 poor areas, most of them located in the suburbs of major metropolitan areas. A parallel that comes to mind with this unprecedented phenomenon for France are the 1965 Watts riots in the US. At that time, the Kerner Commission (1968) identified local unemployment as a major cause of social unrest, and pointed at its potential determinants: geographic isolation and bad physical job accessibility. These ideas have been much studied in the literature on the US over the past four decades (see the surveys of Jencks and Mayer, 1990, Kain 1992, Ihlanfeldt and Sjoquist, 1998, and Gobillon, Selod and Zenou, 2007). In France, the same type of explanations have recently been put forward by the Council of Economic Advisors (Fitoussi, Laurent, and Maurice, 2004): workers residing in distressed and isolated areas simply do not have enough job opportunities.

To explore this idea, this paper estimates the effects of residential segregation and disconnection from jobs on the labor-market transitions out of unemployment in the Paris region. The contributions of the paper to the international literature on the topic are fourfold. First, we use the Labor Force Survey (LFS) that offers a unique sampling scheme by exhaustively surveying all residents in very small neighborhoods (sometimes down to the block level), which allows us to construct contextual indices at a very fine spatial scale. Existing studies on local unemployment use data at a larger scale that is at best the census tract (Weinberg, 2000, 2004), one exception being Bayer, Ross and Topa (2005) who use data at the block level. Second, since the LFS is panel, we are able to study unemployment in a dynamic setting. This type of study is still quite scarce in the literature (exceptions being Holzer, Ihlanfeldt and Sjoquist, 1994, Rogers, 1997, Dawkins, Shen and Sanchez, 2005). Third, we address the problem of potential location endogeneity. This is done generalizing the existing literature on sensitivity analysis (Rosenbaum and Rubin, 1983, Harding 2003) to multiple locations and multiple discrete outcome settings. Fourth, this paper adds to the recent literature in Europe which is still emerging (see Fieldhouse, 1999, for the UK, Aslund, Osth and Zenou, 2005, for Sweden, Dujardin, Selod and Thomas 2005, for Belgium, and Dujardin and Goffette-Nagot, 2005, for France).

The structure of the paper is as follows: in a first section, we present the main theories according to which residential segregation and physical disconnection from jobs can impede unemployed workers from finding a job when they reside in disadvantaged areas. In a second section, we present stylized facts on the Paris region. We show that, on average, local unemployment goes along with residential segregation but not necessarily with bad job accessibility. In a third section, we present our microeconometric study of the effect of the local context on the labor-market transitions out of unemployment. We show that unemployed workers residing in segregated neighborhoods experience serious additional difficulties in finding a job. We find that this result is robust to biases induced by a potential endogeneity of location. A fourth section concludes.

2 Residential segregation and access to jobs: a brief survey of the literature

We present a selective review of the literature that shows how residential segregation and bad job accessibility can deteriorate labor-market outcomes. We leave aside the origins of segregation and the physical disconnection from jobs as this is not the focus of the paper (for details on the causes of segregation and disconnection from jobs, see Gobillon et al., 2007).

2.1 The effects of residential segregation

A first trend of literature stresses the potentially harmful role of residential segregation on the economic outcomes of poor-area residents. The main arguments are threefold: residential segregation deteriorates employability, it reduces the quality of the social newtorks used in job-search activities, and it spurs labor-market discrimination. This subsection briefly surveys the theories and intuitions that support these assumptions.

2.1.1 The low employability of segregated workers

The economic and sociological literature identifies two main channels according to which which residential segregation can strongly deteriorate the employability of residents in poor areas.

The first channel involves the *emergence and diffusion of social problems in segregated areas* in line with the "epidemic theory of ghettos" (Crane, 1991) which recognizes that social problems are endogenously determined and that, once a given threshold of local social deterioration has been reached, the neighborhood is likely to face a severe outburst of social problems. This occurs in the presence of a local externality when the propensity of a young individual to adopt a deviant behavior (e.g. becoming pregnant, dropping out of school, or indulging in criminal activites) is an increasing function of the proportion of same-behavior individuals in the neighborhood. The local contagion effects that explain this pattern are well documented (Case and Katz, 1991). Their prevalence is all the more increased as adults in these areas are themselves socially excluded and do not provide an image of success with whom youngsters could identify (Wilson, 1987).

The second channel involves *the difficulties faced by segregated residents to acquire human capital*, a phenomenon which finds two types of explanations. The first explanation is that segregation exerts a negative externality on the learning process and deteriorates the quality of education acquired in schools (Benabou, 1993). Several studies, indeed, confirm the existence of *peer-group effects* in the production of education and find that a child's success depends on the socio-economic characteristics of other students in the class or in the neighborhood (see e.g. Jencks and Mayer, 1990, Ferguson, 1991, Hoxby, 2000). Focusing on the French case, Goux and Maurin (2004) show that the local concentration of children with difficulties at school increases the individual risk of educational failure —measured by the probability of repeating a grade—. Consequently, in areas where many students perform badly, human capital externalities can further deteriorate the educational achievements of all the children in the area. The second reason why segregation may cause bad educational outcomes is that it often generates low *public* *investments in educational inputs.* In France, where education is overwhelmingly public, the Ministry of Education is often blamed for placing young teachers with little or no work experience in poor areas while more experienced teachers are not required to work in such places (Piketty, 2004). In France, the spatial concentration of poor families also reduces local tax bases (Gilbert, 2004) and makes it difficult to finance key local public goods that are needed for educational purposes such as libraries, stadiums or theatres.

2.1.2 The low quality of social networks in segregated neighborhoods

Another adverse effect of residential segregation is to deteriorate the quality of the social networks unemployed workers can mobilize in order to find a job. This is a crucial problem for distressed areas given that a significant portion of jobs is usually found through personal contacts (Mortensen and Vishwanath, 1994) especially among low-skilled workers, young adults and ethnic minorities who largely resort to informal research methods (Holzer, 1987, 1988). In this respect, the spatial concentration of unemployed workers exerts a negative externality which amplifies the probability of unemployment. In particular, a job seeker residing in a high-unemployment neighborhood knows very few occupied workers —if any at all— that could personnaly support a job application with their employer or that could gear them towards other professional contacts (Reingold, 1999, Selod and Zenou, 2001 and 2006).

2.1.3 Neighborhood stigmatization and redlining

A third link between segregation and bad labor-market outcomes involves a particular type of labor discrimination based on an applicants' place of residence. The main argument is that residential segregation —along a variety of dimensions covering the spatial concentration of unemployed workers, ethnic minorities, low-skilled workers and social housing— can result in the collective perception of "good" and "bad" neigborhoods and influence the hiring behavior of employers. This stigmatization of neighborhoods is at the root of a discriminating behavior —known as "redlining"— in which employers discriminate against the residents of distressed areas just as if their neighborhood had been circled in red on a map.[1]

In theory, there are two principal motives that explain redlining. Firstly, redlining may reflect an employer' subjective hostility or "taste for discrimination" (Becker, 1957) towards the residents of some neighborhoods, rejecting their manners and habits (i.e. language, dress code, imputed social and religious behavior). This hostility is sometimes grounded on the preferences of the customers themselves who could be reluctant to have contacts with employees residing in stigmatized areas. Secondly, redlining may also occur in the absence of any prejudice when employers have imperfect information on the candidates but use their neighborhood of residence as an indication of productivity. This "statistical discrimination" (Phelps, 1972) is detrimental to distressed areas when employers impute lower working abilities to their residents.

In France, redlining or a so-called "*délit de sale adresse*" is often denounced in the popular press but remains

[1] Another type of redlining that has labor-market consequences occurs on the credit market. All things else being equal, if loan applications are more likely to be rejected when originating from distressed areas, then entrepreneurs who want to open a business or to expand their activities may be impeded in their recruitment prospects.

empirically little studied. To our knowledge, the only work that tests the existence of redlining in France is Amadieu (2004) which shows that same-skill candidates applying for a given job obtain less interviews when pretending to reside in le Val Fourré —a highly stigmatized neighborhood in the suburbs of Paris— than when pretending to reside in central Paris.[2]

2.2 The effects of the physical disconnection from jobs

A second trend of literature argues that the physical disconnection between places of residence and places of work can have adverse labor-market outcomes, an intuition known as the "spatial mismatch hypothesis" in the US context but which may also apply to other contexts. This assumption is supported by two different types of arguments which respectively focus on job search and commuting costs.

2.2.1 Distance to jobs, job search and unemployment

Three different mechanisms argue that job search is inefficient, little intense and costly for the unemployed workers who reside far away from job opportunities.

Firstly, the inefficiency of distant job search can be caused by informational frictions when the available information about job vacancies decreases with distance to job opportunities (Rogers, 1997, Ihlanfeldt and Sjoquist, 1990, Ihlanfeldt, 1997, Wasmer and Zenou, 2002 and 2005). One reason is that many firms seeking to fill in a vacancy for a low-skilled position mainly resort to recruitment methods with a limited spatial span such as posting "wanted" signs in shops or having job openings advertised in local newspapers (Turner, 1997). Another reason is that job seekers have difficulties identifying potential employers located in distant zones with which they are unfamiliar. In this respect, Davis and Huff (1972) believe that job seekers only search efficiently within a restricted perimeter around their residences even if this zone only hosts poorly remunerated low-skilled jobs.

Secondly, the low intensity of the job-search effort among job seekers distant from job opportunities can be explained by an indirect argument based on housing prices: because accessibility is bad in places distant from jobs, housing prices in these locations tend to be relatively lower, providing too little incentives for local job-seekers to search actively. On the contrary, the unemployed workers who live close to jobs should be more impatient to find a job in order to be able to pay their rents (see Smith and Zenou, 2003, for a model, and Patacchini and Zenou, 2006, for an empirical investigation).

Lastly, the cost of job search —which increases with distance— may limit the spatial span of job search. Indeed, unemployed workers can give up searching far away from their residences when the costs associated with job search become too large (Ortega, 2000).

[2] In France, non-spatial forms of discrimination remain more studied (see e.g. Bataille, 1997). Recent trials suggest that sheer racial or ethnic discrimination is also a widespread phenomenon.

2.2.2 Commuting and unemployment

The physical disconnection between places of residence and job locations imply long and costly commuting trips, which may generate adverse labor-market outcomes.

The main argument stresses that unemployed workers must consider the offered wages *net of transport costs* when deciding to accept or reject a job offer so that, if tranport costs are very large, workers are likely to reject many job offers and remain unemployed or accept jobs that are poorly remunerated but located close to their residences (Brueckner and Martin, 1997, Coulson, Laing and Wang, 2001, Brueckner and Zenou, 2003). This can be a central issue for unskilled workers who do not own a car and who reside in areas where the public transport system is of low quality (as a result of incomplete network coverage, long waits at interconnection nodes, or the lack of coordination between transport modes).[3] In particular, the unskilled workers eligible for part-time jobs or who would be required to work very early in the morning or late at night may be confronted with low public transport frequencies, if not with the closing of the network at the times when they would most need it.

A second argument that links commuting costs and unemployment has employers discriminate applicants who live far away. This behavior can be understood if distance deteriorates productivity for instance because distant workers are likely to come to work tired or arrive late because of transportation problems (Zenou, 2002).

3 Residential segregation and disconnection from jobs in the Paris region

Keeping in mind the theories and intuitions presented in the previous section, we now discuss a selection of relevant descriptive statistics for the year 1999. All the data we give are for the Paris region —that the French call *Ile-de-France*—, an administrative unit of km^2 $12,072$ which hosts 10.9 million people distributed over $1,300$ municipalities centered around the historic city of Paris.[4] The Paris region —which hosts 11.1 million people— broadly corresponds to the statistical definition of the Paris urban area. The historic city of Paris itself groups 20 of these munipalities (the so-called 20 *arrondissements* of Paris) and is home of 2.1 million residents. It is only a small part of the metropolitan area's *urban core* which also includes 395 surrounding municipalities and hosts a total of 9.6 million residents. Most of the 885 remaining municipalities in the Paris region belong to the metropolitan area's *periurban ring* and a few of them are rural.[5]

[3]For a theoretical paper on public under-investment in transport systems, see Brueckner and Selod (2006).

[4]In France, a municipality (*commune* in French) is the smallest autonomous administrative subdivision that exists. Urban areas typically spread over several municipalities.

[5]A widely used administrative breakdown of the Paris region that we represent on our maps divides the whole region in 8 districts (called "*départements*" in French). At the center of the region, the 20 municipalities of the historic city of Paris form one district. Clockwise around Paris are the Hauts-de-Seine (west), the Seine-Saint-Denis (north east) and the Val-de-Marne (south east). The combination of these three districts forms the *inner ring* ("*petite couronne*") which more or less corresponds to the metropolitan area's *urban core*. The remaining peripheral districts are the Yvelines (west), the Val d'Oise (north), the Seine-et-Marne (east), and the Essonne (south). Together, they form the outer ring ("*grande couronne*") which is essentially made of *periurban municipalities* and of

The most striking fact are the large differences in local unemployment rates across municipalities and the high concentrations of unemployment in just a few areas. Map 1 shows that local unemployment rates are much higher in the north-east of Paris and in the municipalities located to the north and to the north east out of Paris (i.e. in most of the municipalities in the Seine-Saint-Denis district and in some municipalities in the south of the Val-d'Oise district).

[*Insert Map* 1]

As we are interested in how segregation and job accessibility relate to unemployment, we now present a selection of descriptive statistics to assess the intensity of the two phenomena in the Paris region, and of their association with local unemployment rates.

3.1 Segregation measures

We measure residential segregation along three dimensions: education, occupation, nationality.

We first measure the extent to which the residences of workers are spatially segregated along education levels. Our measures of segregation include both local specialization indices and global dissimilarity indices. For a given subgroup of the population and for each municipality, the local specialization index is given by the ratio of the proportion of individuals residing in the considered municipality that belong to the subgroup to the proportion of individuals in the whole region that belong to the same subgroup. When the specialization index takes a value greater than one, the group is locally over-represented in the municipality. Map 2 graphs the specialization index for educated workers in all municipalities and shows that they are over-represented in the city of Paris and in the west of the Paris region (namely in municipalities in the Hauts-de-Seine and Yvelines districts). On the contrary, low-educated workers are over-represented in the rest of the region. The segregation pattern is quite similar when one considers occupation according to the French official job-positions scale that distinguishes high-skilled white collars ("*cadres*") from clerks ("*employés*") and from blue collars ("*ouvriers*"). High-skilled white collars are over-represented in the West. Blue collars are over-presented in the rest of the region. Clerks are frequently over-represented in inner-ring municipalities (see Gobillon and Selod, 2004, for the corresponding maps).

[*Insert Map* 2]

The dissimilarity index (Duncan et Duncan, 1955) is of a different nature. It provides a global measure of segregation between two types of occupations, yielding a single figure that measures segregation across all municipalities between these two types. The dissimilarity index, which lies between 0 and 1, compares the spatial distributions of two occupations by measuring the proportion of individuals from one of the groups that would have to be relocated to other municipalities in order to have the two groups mixed in the same proportion in each municipality.[6] Table

a few rural ones.

[6] The dissimilarity index is given by the formula $\frac{1}{2}\sum_{k}\left|\frac{J_{ik}}{J_i}-\frac{J_{jk}}{J_j}\right|$, where k is the municipality, J_{ik} (resp. J_{jk}) is the number of occupied workers with job occupation i (resp. j) residing in municipality k, J_i (resp. J_j) is the total number of occupied workers with job occupation i (resp. j) in the whole Paris region.

1 presents the dissimilarity indices for our three combinations of occupations taken two by two. Observe that the levels of segregation between high-skilled white collars and blue collars, and between high-skilled white collars and clerks, are the highest: it would be necessary to relocate 39% (resp. 26%) of high-skilled white collars to other municipalities in order to obtain a constant ratio of high-skilled white collars and blue collars (resp. clerks) in each municipality. Also oberve that segregation is stronger in the inner ring than within Paris or across municipalities within the outer ring.[7]

[*Insert Table* 1]

When computing segregation indices for nationalities, we chose to focus on Maghrebines and Africans (i.e. Africans that are not Maghrebines) as these two groups form the bulk of disadvantaged minorities in France.[8] Map 3 shows that both Maghrebines and Africans (excluding maghrebines) are concentrated to the north of Paris (in the Seine-Saint-Denis district and the southern part of the Val-d'Oise district) as well as to the south of Paris (in the western part of the Val de Marne district). Table 1 confirms that Maghrebines and Africans are significantly segregated from the French since enforcing a uniform residential mix with the French would require to relocate 32% of individuals that belong to these two groups. Interestingly, Maghrebines and Africans are not distributed very differently across space and reside in the same areas since the dissimilarity index between them is only .13.

[*Insert Map* 3]

Segregation by diploma is not as stark as segregation by job occupation or by nationality. Only 25% of the educated labor force (i.e. workers holding at least a high school diploma) would have to be relocated to other municipalities if one wanted to obtain a uniform residential mix of educated and uneducated workers in each municipality (see Table 1).

Considering all these dimensions (occupations, nationalities, and diplomas), Paris appears to be a more integrated area than the inner and outer suburban rings as segregation indices are always lower within Paris (i.e. across Paris districts).

Now, having identified different types of residential segregation, we can measure the association between segregation and unemployment in the Paris region. We find that the unemployment rate is strongly correlated with the local composition of each municipality. Indeed, the correlation between the unemployment rate and the proportion of high-skilled white collars is $-.54$. The correlation between the municipality unemployment rate and the proportion of Africans (including Maghrebines) stands at .85.[9]

[7] For comparaison, Cutler, Glaeser and Vigdor (1999) who measure black/white segregation in american MSAs consider that segregation is low when the dissimilarity index is below .3, that is is medium when the index is between .3 and .6, and that it is high when the index is above .6. With this grid of analysis, our measures would indicate only a low or medium level of segregation. However, Cutler et al. use a finer spatial breakdown (the census tract) than we do, and it is well-known that segregation indices usually decrease with the size of the geographic units considered. By comparing segregation indices at different spatial levels, Préteceille (2003) checked that this decreasing pattern is also the case in the Paris region.

[8] In France, the collect and use of racial or ethnic statistics are forbidden by law so we are constrained to work on nationalities.

[9] All the correlations in this subsection and in the the following one are computed weighting the observations by the labor force in

3.2 Job-accessibility measures

We measure the disconnection between places of residence and job locations in two different ways, with the calculation of global dissimilarity indices and local ratios of labor demand and supply.

The dissimilarity indices we compute compare the spatial distribution of workers and that of jobs. In Table 2, we report the indices for all workers and all jobs but also by occupation type, nationality and diploma.[10]. The dissimilarity index between all workers and jobs is .25, but this figure conceals differences by occupation type. For high-skilled white collars and their corresponding jobs, the index reaches .31, whereas for clerks, it stands at .30, and for blue collars, it is .25. Observe that blue collars exhibit the lowest disconnection from jobs because of the decentralization of manufacturing firms to the inner and outer rings where blue-collar workers traditionally reside —and where land is cheaper and space readily available—. The dissimilarity indices by nationality also reveal stark differences. With a value of .33, it is highest for Africans (excluding Maghrebines) and the jobs they occupy, but stands only at .26 for Maghrebines, very close to the value of the index for the French (.25). Interestingly, focusing on dissimilarity indices by educational level, we obtain the same value of the index (.26) irrespectively of whether we focus on educated workers and jobs (i.e. with a high school diploma) or on uneducated workers and the corresponding jobs.

[*Insert Table* 2]

A second approach measures the ratio of available jobs to resident workers (whether occupied or not) within a 45-minute commuting trip around each municipality. This is the most simple way of capturing the tension on a local labor market centered on each municipality. In Appendix A, we present two alternative indicators based on refined assumptions on the local labor demand and supply. The reason we have chosen a 45-minute cut-off is that it is slightly above the average commuting time to work in the Paris region (which stands at 34 minutes in 1997 according to DREIF-INSEE, 1997). We believe it approaches the relevant area within which a worker would accept a job without a residential move. The indicator is computed using job and worker locations from the 1999 Census of the Population and the commuting times between municipalities estimated at morning peak hours in 2000 by the Ministry of Transport for both public and private transport modes.[11]

Job densities within 45 minutes using public tranport are represented on Map 4. It can be seen that job accessibility by public transport is very good in Paris, in the north of the Hauts-de-Seine district, in the west of the Seine-Saint-Denis district and in the west of the Val-de-Marne district. In these areas, each municipality is the center of an isochron inside which there are 1.2 to 2 times more jobs than workers. Map 5 shows that job

each municipality.

[10] For occupation types, dissimilarity indices are computed on *occupied* workers and the corresponding jobs. This is because, by definition, unemployed workers have no job occupation. By contrast, when computed for a particular educational level or nationality, our dissimilarity indices measure the disconnection between all workers of the considered type (whether occupied or not) and the corresponding jobs.

[11] Matrices of commuting time between municipalities were estimated by the Ministry of Transport (*Direction Regionale de l'Equipement Ile-de-France*) using the General Transport Survey (*Enquête Globale des Transports*, 2000). For a detailed description of this data and their use to calculate other accessibility indices, see Wenglenski (2003).

accessibility is on average lower by private vehicle than with public transport (because of freeway congestion). Job accessibility is better in and around Paris (except to the east) and to the west, including in the outter ring. To summarize the information given by the maps, we also computed the average density reachable in 45 minutes for all the municipalities in the Paris region, in the inner and outer rings, and in the historic city of Paris (weighting by the local labor force). Table 2 confirms that access to jobs is on average better by public transport than with private vehicles, and that it decreases when moving away from Paris. We also computed job-accessibility indices separately for uneducated and educated workers (i.e. without and with a high school diploma). Job accessibility by private vehicle is not as good for uneducated workers than for educated ones. Conversely, job accessibility by public transport is better for uneducated workers than for educated workers in Paris and in the inner ring.

$$[Insert\ Maps\ 4\ and\ 5]$$

We finaly examine the correlations between unemployment and our measure of access to jobs. The unemployment rate is not correlated with the density of jobs that can be reached within 45 minutes by private vehicle (the correlation being only .01) but it is positively though weakly correlated with the density of jobs that can be reach by public transport within the same time span (with a correlation of .15). *A priori*, this suggests that unemployed workers may not suffer from a poor access to jobs in the Paris region.

4 The econometric setting

The stylized facts we just presented showed that there are large unemployment disparities among the region's municipalities. Areas where the unemployment rate is high usually exhibit a high level of segregation but not necessarily a spatial disconnection from jobs. Using individual, we now study data how the local context (segregation and job accessibility) can affect the labor-market transitions out of unemployment. Studying transitions rather than the cross-section labor-market status (i.e. being unemployed or occupied at one point in time) as in Dujardin, Selod and Thomas (2004) makes the interpretation of the results easier because the job-search mechanisms that we described in Section 2 are dynamic by definition.

4.1 The data

The dataset

Studying the effect of the local context on the transitions out of unemployment requires panel data with information on the place of residence at a fine geographical scale. To our knowledege, the French Labour Force Survey (LFS) is the only data source that can be used for this purpose. This dataset is a rotating panel where individuals are surveyed yearly over a three-year period but only if they do not move. If they move, they disappear from the panel. The sampling scheme consists in surveying tiny neighborhoods of nearly twenty households living in adjacent dwellings (see Goux and Morin, 2004 for a more detailed description of the sampling scheme). All individuals older than 15 are surveyed. The dataset contains the usual socio-demographic information (sex, age, diploma) as well as variables on unemployment and employment spells. We selected only workers that are unemployed (according to the definition of the International Labour Organization) and who reside in the Paris region.[12] We then constructed the yearly transitions over the 1990-2002 period that correspond either to a labor-market transition or to an exit from the dataset that occurred too early (because of a move, death, non-response, etc.). We obtained a final subsample of $9,643$ transitions of four types: remaining unemployed (33.7%), finding a job (26.2%), leaving the labor force (13.9%) and disappearing from the dataset too early (26.2%). The first three types of transition are implicitely not associated with any residential move. To the contrary, the fourth type of transition mainly corresponds to residential moves.[13] The location of unemployed workers experiencing a transition are distributed across $3,905$ neighborhoods-years; the surveyed neighborhoods being located within 371 muncipalities of the Paris region, mainly in the urban core, i.e. in the hitoric city of Paris and in the inner ring. Map 6 represents the number of transitions in each muncipality over the whole period.

[*Insert Map* 6]

The local context

Thanks to the spatial cluster structure of the LFS survey, we are able to compute contextual measures of the immediate neighborhood with which unemployed workers are likely to interact when looking for a job.[14] For each neighborhood, we computed the proportion of high-skilled white collars, the proportion of educated workers in the labor force (i.e. having a high school diploma), the rate of Africans (including Maghrebines), and the unemployment rate. It would have been desirable to also compute a job accessibility measure at the neighborhood level but data required for this are not available. Descriptive statistics at the neighborhood-year level are reported in Table 3. The number of observations by neighborhood-year varies from 1 to 109, with an average number of 27 observations.

[*Insert Table* 3]

We also constructed the same proportions at the municipality level using the data from the 1999 census. We report in Table 4 the correlations between the indices computed at the neighborhood-year level for the 1990-2001 period and at the municipality level in 1999. All the correlations are computed weighting the observations by the number of transitions observed for each neighborhood-year. They characterize the local environment of the surveyed unemployed workers in the LFS at two different spatial scales.

At the municipality level, the proportion of high-skilled white collars is negatively correlated with the proportion of Africans (-.47). This means that when municipalities where unemployed workers live exhibit a large proportion of

[12] According to the *ILO* definition, an unemployed worker is an individual old enough to work (i.e. over fifteen years of age), available to work and looking for a job.

[13] Using the French LFS, Desplanques (1994) estimates that, for women aged between 20 and 64, 85% of the exits from the dataset that occur too early are due to a residential move.

[14] Héran (1987) shows that the spatial span with which individuals declare to have social interactions decreases with population density. In Paris for instance, 80% of the households declare that they only interact with neighbors in their building. It is likely that the spatial span of the French LFS's clusters, which is small and also diminishes with density, approximates the relevant neighborhood scale for social interactions.

high-skilled white collars, they tend to have a small proportion of Africans. The correlation between the proportion of high-skilled white collars and our index of job accessibility by private transport are strongly positively correlated (0.60). By contrat, the correlation between the proportion of Africans (including Maghrebines) and the density of jobs that can be reached using a private vehicle is lower (.17). The correlation between the percentage of high-skilled white collars and the job density that can be reached by public transport within 45 minutes is .32. The correlation between the percentage of Africans (including Maghrebines) and the job density that can be reached by public transport is also .32.

At the neighborhood scale, the correlation between the proportion of high-skilled white collars and the proportion of Africans is $-.35$. Moreover, neighborhood variables are strongly correlated with variables of the same type at the municipality level. In particular, the correlation between the proportion of neighbors that are high-skilled white collars and the proportion of high-skilled white collars in the municipality is .60. The correlation for the neighborhood and municipality proportions of Africans (including Maghrebines) is .48. These correlations are quite high but still suggests some heterogeneity between neighborhoods in a same municipality.

[*Insert Table* 4]

To better characterize neighborhoods, we classify them along the following three dimensions: neighborhood segregation, municipality segregation and job accessibility. To do that, we run a separate hierarchical ascending classification (HAC) for each dimension keeping only two classes each time. For neighborhood segregation, the HAC is built from the neighborhood proportion of educated workers and that of Africans. The two classes oppose segregated neigborhoods to non-segregated neighborhoods (see Table 5a). For segregation at the municipality level, the HAC is built from the municipality proportion of educated workers and that of Africans. The two classes oppose neighborhoods in segregated municipalities to neighborhoods in non-segregated municipalities. For job accessibility, the HAC is built from job densities by private and public transport. The two classes oppose neighborhoods in municipalities with good job acessibility to neighborhoods in municipalities with bad job acessibility. Crossing the three HAC, we construct an eight-class typology of neighborhoods which is described in Table 5b. In every municipality, we find that at least 50% of the LFS transitions occur in a given neighborhood type. Map 7 represents the prominent type across municipalities. Consistenly with the stylized facts presented in the previous section, we see an opposition in the degree of neighborhood and municipality levels of segregation and between the west and the north-east of Paris and its inner ring. The north-east where segregation is strong is split between municipalities close to Paris that have a good job-accessibility and those further away that have a bad job accessibility.

[*Insert Tables* 5*a and* 5*b*]

[*Insert Map* 7]

4.2 The model

It would be natural to study unemployment in a dynamic perspective using an unemployment duration model but our data provides only incomplete coverage of unemployment spells. In this context, estimating a duration model would be feasible but very burdensome and in any case not completely satisfactory as duration dependence would not be considered (see Magnac, Robin and Visser, 1995). Instead, we study the labor-market transitions of unemployed workers with a discrete-choice model. It would be tempting to resort to panel data techniques (with individual random or fixed effects) but this would require to observe mutliple transitions for each type of exit out of unemployment. This is not possible for transitions from unemployment to employment or inactivity which can be observed at most once with three consecutive yearly observations. We thus simply use a multinomial model with latent variables corresponding to $E = 4$ types of exits: remaining unemployed ($e = 1$), finding a job ($e = 2$), dropping out of the labor force ($e = 3$), and disappearing from the dataset ($e = 4$). For a worker i at time t (as each individual can experience up to two transitions over the period), the exit is the result of a random variable denoted E_{it}. The latent variable associated to any exit e writes:

$$E^*_{it,e} = X_{it}\alpha_e + Z_{jt}\beta_e + \varepsilon_{it,e} \tag{1}$$

where X_{it} is the set of individual explanatory variables at time t (assumed to be exogenous), j is the worker's LFS neighborhood at the beginning of the transition. Observe that, since movers are not followed, when an individual experiences two transitions (i.e. appears at three consecutive dates in the panel), his location does not change. Z_{jt} is the set of aggregate explanatory variables for location j at time t, and $\varepsilon_{it,e}$ is a random shock. Here, j can be viewed as a draw of a random variable L_i that accounts for the location choice of a worker i. As we are interested in measuring the effect of the explanatory variables X_{it} and Z_{jt} on the labor-market transitions out of unemployment, we choose exit $e = 1$ as a reference and impose the restrictions $\alpha_1 = 0$ and $\beta_1 = 0$. We also assume that the random shock $\varepsilon_{it,e}$ is independent from the observable characteristics X_{it} and Z_{jt}.

Assume for the time being that the location L_i is independent from the random shock $\varepsilon_{it,e}$. The location choice is then exogenous. We choose to specify $\varepsilon_{it,e}$ as following an extreme-value law (conditionally on the observables) so that we finally obtain a multinomial logit for the different exits where the probability that the individual i experiences an exit E_{it} of type $e \in \{2, 3, 4\}$ writes:

$$P\left(E_{it} = e\,|X_{it}, L_i = j, Z_{jt}\right) = \frac{\exp\left(X_{it}\alpha_e + Z_{jt}\beta_e\right)}{1 + \sum\limits_{e=1,2,3} \exp\left(X_{it}\alpha_e + Z_{jt}\beta_e\right)} \tag{2}$$

We estimate the model at two different geographic scales. In the first specification, the geographic scale is the neighborhood ($J = 2,424$). In this case, the variables Z_{jt} include our job-accessibility and segregation variables both at the neighborhood and the municipality levels. In the second specification, the geographic scale is the HAC cluster ($J = 8$). In this case, the Z_{jt} variables only include seven location dummies (one cluster being chosen as a reference).

4.3 The sensitivity analysis

A major issue is that the estimates of (2) can suffer from a selection bias if unemployed workers sort themselves spatially along some unobservables. More precisely, spatial sorting appears when there are individual unobserved factors that simultaneously have an effect on the labor-market transition and the location choice. Put differently, the location L_i may be correlated with the random shock $\varepsilon_{it,e}$ and the location is then endogenous. An approach to overcome this problem could be to estimate an econometric model that would simultaneously explain the transition on the labor market and the location choice. This model should allow for a correlation between the individual unobservables introduced in the transition and location specifications. Nevertheless, the estimation of such a model would be problematic for two reasons. First, a method for estimating a model with multiple outcomes and multiple locations has only been proposed in the case where the outcome is continuous (Dahl, 2002). Second, even if such a method were available, identifying the model without relying on non-linearities would require an exclusion restriction such that some variables explaining location have no direct effect on labor-market transitions. Finding such variables is very difficult. Given these problems, we choose to use two alternative strategies to address the endogenity of location:

The first strategy follows Goux and Maurin (2004) and checks that our results are robust when reestimating the model only on the subsample of unemployed workers living in public housing. Indeed, one can think that their location is exogenous given that offers for a public dwellings are made by public-housing offices without taking into account the preferences of applicants for locations. Two criticisms however should be kept in mind. First, it is possible that some individuals reject a housing offer and prefer to wait for another one that better fits their preferences (Dujardin and Goffette-Nagot, 2005). The endogeneity problem then still occurs, for instance if individuals with valuable unobservable characteristics (i.e. that improve their chances to find a job), more frequently reject housing proposals for suburban public dwellings where finding a job is more difficult. Second, unemployed workers living in public dwellings may have unobservable characteristics that make it more difficult to find a job. Hence, considering only individuals in public housing introduces a selection bias in the analysis.

The second strategy is a sensitivity analysis which goal is to evaluate the endogeneity bias created by an unobserved individual variable that would affect both locations and transitions. We build on Rosenbaum and Rubin (1983)'s approach for a binary logit model which was applied to test the robustness of local effects by Harding (2003) and Dujardin, Selod and Thomas (2005). In this type of method, the key idea is to jointly model the transition and location choices. The location endogeneity problem is accounted for by introducing a same unobserved individual variable both in the transition model and the location choice model. The law of this unobserved variable may be specified in different ways: it can be continuous or discrete—multinomial or, in particular, binary— and is considered as known. Its effects in both the transition and location specifications are drawn in a given range of values. The effects of explanatory variables in the transition equations (and specifically those of local variables) are then reestimated. We assess whether these reestimated effects differ from those obtained with the simple multinomial logit model without individual unobserved heterogeneity.

In the transition equation (1), for each exit e, the shock in the labor-market transition is split between the effet of the unobserved individual variable u_i and a random component $\eta_{it,e}$:

$$\varepsilon_{it,e} = \gamma_e u_i + \eta_{it,e} \tag{3}$$

where γ_e measures the effect of the unobserved variable on the transition and $\eta_{it,e}$ follows an extreme-value law.

The location choice among possible locations is assumed to follow a logit specification conditionally on the unobserved and observed individual variables. In this model, denoting t_0 the individual's initial transition date, the latent-variable equation for location $j \in \{1, ..., J\}$ is specified as:

$$L^*_{i,j} = A_{it_0}\lambda_j + B_{jt_0}\theta + \delta_j u_i + \nu_{i,j} \tag{4}$$

where A_{it_0} is a set of individual observed characteristics at date t_0 with effects λ_j, B_{jt_0} is a set of observed aggregate characteristics at date t_0 with effects θ, δ_j is the effect of the unobserved individual variable and $\nu_{i,j}$ follows an extreme-value law. Observe that the effects of the observed and unobserved indivividual variables (λ_j and δ_j respectively) can depend on location.

The complete model finally includes equations (1), (3) and (4). The endogeneity issue is due to the fact that the unobserved individual variable has an effect simultaneously in the labor-market transition equations (1) *via* (3) and in the location-choice equations (4). It appears only if the coefficients γ_e and δ_j are simultaneously different from zero and if there is some variation in the value taken by the individual unobserved variable among unemployed workers. The analysis consists in estimating the effects of individual and agregate explanatory variables (α_e and β_e) in (1) under alternative assumptions on the effects of the unobserved individual variable (γ_e and δ_j). Observe that, since the unobserved heterogeneity coefficients are fixed —and not estimated— no exclusion restriction is needed (Altonji, Elder and Taber, 2005). There is no need to have a variable in A_{it_0} or B_{jt_0} that is not in X_{it} or Z_{jt}.
The procedure can be decomposed into two successive steps:

- We draw the coefficients of the individual unobserved variable in the transition specification (γ_e) and in the location specification (δ_j) in some given specified laws.
- We reestimate the model by full maximum likelihood. This finally gives the effects of the explanatory variables in the transition equations (1).

The methodological details are relegated in Appendix B. In our application, we carry out the sensitivity analysis only for the transition specification with cluster dummies ($J = 8$). This is because performing the sensitivity analysis on $J = 2,424$ locations would have required a much greater number of transitions than what our sample provided. The objective being to assess how the coefficients in the transition equations vary under different endogeneity patterns, we repeat the procedure $S = 1,000$ times. We report some descriptive statistics on the coefficients obtained from the different simulations. In particular, we examine to which extent the coefficients obtained in our simulations are of the same sign and significance as those obtained from the estimation of (2) when endogeneity is not accounted for. The application details are presented in appendix B.

4.4 The results

4.4.1 A regression with segregation and job-accessibility indices

We first present the results when estimating the multinomial logit model (2). The reference category for transitions is "remaining unemployed and not moving". The regression includes sociodemographic individual variables, variables related to job search, as well as the local indices measuring segregation and job accessibility. Since segregation indices are highly correlated at the neighborhood and municipality level (see Table 4), we retain in the main regression only two segregation indices which have a significant effect while being little correlated between themselves. One of the indicator is measured at the neighborhood level in order to capture the effects that occur at a fine geographic scale (such as interactions between neighbors). The other indicator is measured at the municipality level in order to capture the effects that occur at a broader geographic scale (such as redlining). This also allows to control for the municipality's composition while estimating the effects of the job accessibility variables. The contextual variables that we retain are: concerning segregation, the percentage of neighbors in the active population that have a high school diploma and the percentage of Africans in the municipality; concerning job accessibility, the job densities within a 45 minute isochron by private transport and by public transport.

In Table 6a, we report the estimated coefficients and the corresponding odds-ratios. We first comment the effects of individual characteristics on the different transitions.

Technical and university diplomas increase the probability of finding a job while having a general high school diploma but no other diploma reduces it. Nationality also plays a role: being Maghrebine or African (but not Maghrebine) diminishes the chances of getting a job (at the 10% level). Searching for a job through personal methods in addition to being registered with the National Employment Agency increases the probability of finding a job. Interestingly, searching for a job without registering with the National Employment Agency is more fruitful than registering with the National Employment Agency and not resorting to any other job search method. This can be understood if the choice of the search method is selective: those who might easily find a job could be less likely to register with the National Employment Agency.

Concerning "dropping out of the labor force without moving", what is striking is the negative effect of resorting to personal contacts for individuals registered with the National Employment Agency. An explanation could be that unemployed workers that are sufficiently motivated to diversify their job-search methods are less easily discouraged and less likely to drop out of the labor force.

Finally, the category "disappearing from the panel" (an exit which is usually associated with residential mobility) is favored by having a university diploma (at the 1% level), which is consistent with a greater residential mobility of the educated, as previously observed in the literature (Schwartz, 1973). In addition, home owners have a lower relative risk of disappearing prematurely from the panel than renters in the public sector, who themselves have a lower relative risk of disappearing prematurely from the panel than renters from the private sector. These results are comparable to those obtained on residential mobility by Gobillon (2001) on the European Community Household Panel (ECHP).

We now comment the effects of the contextual variables on the three types of transition.

Concerning finding a job, the percentage of educated neighbors (i.e. that have a high school diploma or above) has a positive effect, which is in accordance with social network and neighborhood stigmatization theories. The percentage of Africans in the municipality has a negative effect (although not significant), which is consistent with redlining. Among job-accessibility variables, only the job density within 45 minutes by public transport has a significant effect (at the 10% level) but the impact is negative, which is not consistent with the spatial mismatch theory. This result remains even when looking at jobs accessibility by skill level (see Appendix C). This raises a series of comments. Firstly, problems of job accessibility may not impede unemployed workers from finding a job. This was already suggested by Maps 1 and 4 in which job accessibility is good in municipalities where unemployment rates are high. Secondly, the sign of the effect can be explained by the fact that job densities may capture unobserved individual or local variables detrimental to finding a job. For instance, it is possible that individuals with adverse unobserved characteristics have no other choice than to locate in unattractive suburbs but with a good job accessibility. Conversely, individuals with beneficial unobserved characteristics may locate in attractive suburban residential neighborhoods but far away from jobs. An unobserved local variable detrimental to finding a job but correlated with job density is the congestion of public services (a well-known phenomenon in France). Thirdly, our job density indicators are computed using transport times at the municipality scale, which might occult relevant intra-municipality differences in job-access (for instance when an area is crossed by train tracks but has no train station).

Concerning the transition out of the labor force, none of the contextual variables has a significant effect.

Concerning the premature exit from the panel, the proportion of educated workers in the neighborhood has a positive effect while the proportion of Africans in the municipality has a negative effect (although only significant at 10%). This is consistent with an increased mobility of the individuals that reside in neighborhoods populated with educated workers and in municipalities with a low concentration of Africans.

[*Insert Table* 6*a*]

To test the robustness of the results of our baseline model, we also estimate a series of alternative specifications. Since we use a multinomial logit model, transitions are assumed to verify the independence of irrelevant alternatives. As this may not be the case in practice, we performed a robustness check by estimating a nested logit model where the *ιia* is not *a priori* assumed. The objective is to check that the sign and significance of the effects of local variables is comparable to what we obtained estimating (2). At the first level of the nested-logit model, an individual disappears or stays in the panel ($e = 0$ vs $e \in \{1, 2, 3\}$). At the second level, conditionally on staying, the individual experiences a labor-market transition that can be: remaining unemployed ($e = 1$), finding a job ($e = 2$) or dropping out of the labor force ($e = 3$). This specification allows for a correlation between the transitions $e = 1, 2$ and 3. We obtain results that are very close to those of our baseline model. In particular, the neighborhood proportion of high educated workers has a positive and significant effect on finding a job and disappearing from the panel.[15]

[15] Details are available upon request.

For the baseline multionial logit model (2), we also ran a regression discretizing segregation and job-accessibility variables in order to capture possible non-linear effects. We tried alternative indices of segregation and job-accessibity measures. For job-accessibility, we used indicators computed by level of education. None of these specifications qualitatively altered our findings (for details, see Appendix C).

We finally examined whether the results could be generated by measurement errors due to the small size of some neighborhoods, which would affect the percentages computed at the neighborhood level. This is done by excluding observations that correspond to a neighborhood-year with only a small number of workers. We obtained results similar to those in the main regression.[16]

4.4.2 A regression with dummies for neighborhood type

We also run a regression substituting dummies for the type of neighborhoods (see the previous section for their construction) to the continuous contextual variables. The reference group is the class of neighborhoods with weak segregation both at the neighborhood and municipality levels and a good job accessibility (type I). The results are presented in Table 6b. We find that residing in a neighborhood that differs from the reference group only because it is segregated (type III) reduces the chances of finding a job. Residing in a neighborhood that differs from the reference group only because it has a bad job accessibility (type V) increases the chances of finding a job, of dropping out of the labor force, and of moving (10% level only). This result does not support the spatial mismatch hypothesis for this type of neighborhood, confirming our previous evidence. Residing in a neighborhood that is segregated and located in a segregated municipality and has a bad job accessibility (type VIII), decreases the chances of moving. The effect of living in such a neighborhood on finding a job, although of the expected negative sign, is not significant.

[*Insert Table 6b*]

4.4.3 Accounting for a potential endogeneity of location

We now present the results of our two robustness tests to address the issue of location endogeneity. First, we reestimate our model using the subsample of unemployed workers residing in social dwellings (3,108 transitions for which location "choice" is likely to be exogeneous).

We present the results for the regression with segregation and job-accessibility indices in Table 7a. They are not very different from those obtained for the sample of all unemployed workers (Table 6a). The rate of educated neighbors still has a positive and significant effect on finding a job and on the premature exit from the panel.

[16] When we exclude from the sample the observations which neighborhood-year has a number of workers below the first decile (which corresponds to 12 workers), results are similar to those obtained in the main regression. The only noticeable difference is that the negative effect of job density by public transport on finding a job is now significant at the 5% level. When we exclude the observations which neighborhood-year has a number of workers below the median (which corresponds to 21 workers), results are once again very close to those obtained in the main regression. However, the positive effect of the percentage of educated workers on finding a job is not significant at the 10% level anymore.

The rate of Africans in the municipality has a negative effect on the premature exit from the panel and it is now significant at the 1% level. This suggests that unemployed workers residing in municipalities where the percentage of Africans is high are often less mobile. The density of jobs that can be reached *via* public transport still has a negative effect on finding a job, but this effect is not significant. Finally, it is noticeable that the job density that can be reached by private transport now has a positive effect on exiting the panel (significant at the 5% level) but no significant effect on finding a job. This result suggests that when locations are exogenous, job accessibility *via* private transport may positively influence mobility. Two interpretations seem possible. First, in accordance with the spatial mismatch theory, the unemployed workers who reside in areas where job accessibility is good could have better chances of finding a job, which could involve moving closer to a new place of employment. Alternatively, the local job density could be correlated with unobserved individual or local factors having a positive influence on residential mobility.

The results for the regression that uses dummies for neighborhood type are presented in Table 7b. In comparison with the regression on the whole sample (Table 6b), most coefficients become not significant and even sometimes change sign (without being significant). In particular, this occurs for neighborhoods with a weak segregation and a bad job-accessibility (type V). Note also that the effect of living in a segregated neighborhood with a good job accessibility (type III) still has a negative effect on finding a job but the effect is not significant anymore. Given this accuracy problem, it is hard to conclude from this regression with neighborhood dummies on the subsample of unemployed workers residing in public housing whether there is a location endogeneity issue or not. The accuracy problem may stem from the reduction of the sample size and/or from a lack of variability as we aggregated information through the HAC.

[*Insert Tables* 7*a and* 7*b*]

Our second approach is more elaborate and consists in evaluating a potential endogeneity bias due to an unobserved individual variable that would simultaneously influence the exit from unemployment and the location choice (see section 4.3 and Appendix B). Since carrying out the sensitivity analysis for the model with $2,424$ locations (neighborhoods) would have required many more observations, we focus only on the specification with 8 locations (clusters). We first consider cases in which there is at best a significant but moderate degree of endogeneity, and simulate $1,000$ settings for the effects of individual unobserved heterogeneity .[17] Our results (see Appendix B) show that the coefficients of cluster dummies that were obtained for the multinomial logit regression (2) are usually robust when the endogeneity of location is taken into account. The effect on finding a job of living in a type-III neighborhood (neighborhood segregation) is negative in all the cases and significantly negative in 86% of the cases. The effect on finding a job of living in a type-V neighborhood (bad job accessibility) is positive in all

[17] Indeed, we draw the coefficients of the unobserved individual variable, γ_e and δ_j in $[-\ln 2, \ln 2]$ such that the corresponding odds-ratios are comprised between .5 and 2. For comparison, observe that in our estimation of the baseline transition equations, odds-ratios are comprised between .2 and 2.1 (see Table 6b). In the location-choice specification, they are comprised between .1 and 20.2 (see Table A1).

the cases and significantly positive in 98% of these cases. This suggests that the negative effect of job accessibility is robust when location endogeneity is moderate.

To check what happens in more problematic cases, we replicate the methodology three more times with increasing degrees of endogeneity.[18] Results are easily represented graphically. For instance, for cluster III (neighborhood segregation), Graph 1 plots the percentage of estimated coefficients in labor-market transition equations that are positive and significant (at a 5% level), positive but not significant, negative but not significant, and negative and significant. As expected, for finding a job, the percentage of negative coefficients decreases with increasing endogeneity patterns from 100% to 93%. The percentage of significantly negative coefficients decreases from 86% to 55%. Graph 2 plots the same statistics for the effect of living in cluster V (bad job accessibility) on labor-market transitions. When considering finding a job, the percentage of positive coefficients decreases from 100% to 93% when endogeneity increases. The percentage of significantly positive coefficients also decreases from 98% to 70%. This suggest that our result on neighborhood dummies are fairly robust to location endogeneity issues.

[*Insert Graphs* 1 *and* 2]

5 Conclusion

This paper studies the local determinants of urban unemployment in the Paris region. We present some key stylized facts which characterize the intensity of segregation in the Paris region and differences in job accessibility across the region's municipalities: the locations where the unemployment rate is the highest are also characterized by segregation but apparently not by a bad job accessibility.

We then estimate the effect of the local context on the individual transitions out of unemployment. Our analysis is dynamic and adds to the literature that is mostly cross-section. Another originality of our paper is to use a dataset with a unique sampling scheme that exhaustively surveys all residents in very small neighborhoods. This allows us to construct neighborhood segregation indices at a much finer scale than most previous studies. Our results suggest that neighborhood segregation prevents unemployed workers from finding a job. This could be explained by the low quality of social networks in the neighborhoods where unemployed workers live or by a possible phenomenon of redlining.

We test the robustness of this result to a potential location-endogeneity bias in two different manners. A first approach is to restrict the sample to public housing residents whose location can reasonably assumed to be exogeneous in the case of France. A second approach resorts to a sensitivity analysis that generalizes the existing literature to a setting with multiple discrete outcomes and multiple locations. We find that the negative effect of segregation on finding a job remains.

[18] Technically, we draw $1,000$ simulations such that the odds-ratios for γ_e and δ_j are comprised between $1/3$ and 3, another $1,000$ simulations such that they are comprised between $1/4$ and 4, and yet another $1,000$ bewteen $1/5$ and 5.

Ours results also suggest that segregation has an effect on residential mobility. An interesting issue in this respect is whether residential mobility is associated with an enhanced return to employment. Since our dataset does not offer this possibility, we leave this issue for future research.

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7 Appendix A: Alternative measures of job accessibility

The computation of ratios of local labor demand and supply provides a municipality-wise measure of job-accessibility. It quantifies the possible mismatch between local labor demand and labor supply. We provide three different indicators depending on the assumptions that can be made to compute the local labor supply and demand. All our indices are computed using job and worker locations from the 1999 Census of the Population and the commuting times between municipalities estimated at morning peak hours in 2000 by the Ministry of Transport for both public and private transport modes.[19]

Our first index simply measures the ratio of available jobs to resident workers (whether occupied or not) within a 45-minute commuting trip around each municipality. This is the index we used throughout the present study as its meaning is straightforward. The formula for the index is as follows:

$$A_1^i = \frac{\sum_{j=1}^{N} f\left(d_{ij}\right) E_j}{\sum_{k=1}^{N} f\left(d_{ik}\right) R_k} = \sum_{j=1}^{N} f\left(d_{ij}\right) \left(\frac{E_j}{\sum_{k=1}^{N} f\left(d_{ik}\right) R_k} \right) \tag{5}$$

where i is the considered municipality, N is the number of municipality, E_j is the number of jobs in municipality j, R_j is the number of resident workers in j, and $f\left(d_{ij}\right)$ is a distant decay function with d_{ij} the travel time between i and j (where $f\left(d_{ij}\right)$ is equal to 1 if d_{ij} is equal to or lower than 45 minutes, and 0 otherwise). This indicator is a very simple measure of job accessibility that should be considered only as a first-order approximation of the local labor-market tension in each municipality. Indeed, even though it provides a correct measure of the relevant labor demand (by counting all the jobs that can be reached in 45 minutes or less from location i) it provides only an approximation of the relevant local labor supply by assuming that only the workers who reside within the *same* 45-minute isochron centered on i are competing for these jobs.

To address this issue, we also use a second indicator that was previously proposed by Joseph and Bentock (1982) in another context and which incorporates a more appropriate measure of the local labor supply:

$$A_2^i = \sum_{j=1}^{N} f\left(d_{ij}\right) \left(\frac{E_j}{\sum_{k=1}^{N} f\left(d_{kj}\right) R_k} \right) \tag{6}$$

The main difference with (5) lies in the second term in (6) which better captures the competition for jobs in a municipality j accessible in 45 minutes or less from municipality i. Indeed, for each municipality j accessible within 45 minutes of a municipality i, the local supply term $\sum_{k=1}^{N} f\left(d_{kj}\right) R_k$ is now correctly centered on j and not on i as in (5). It thus correctly considers all the workers that could travel to work in j within 45 minutes. However, the correction for the competion factor is not entirely satisfying as it can be seen from (6) that some workers may be

[19] Matrices of commuting time between municipalities were estimated by the Ministry of Transport (*Direction Regionale de l'Equipement Ile-de-France*) using the General Transport Survey (*Enquête Globale des Transports*, 2000). For a detailed description of this dataset and its use to calculate other accessibility indices, see Wenglenski (2003).

counted several times as they may compete for several jobs within the isochron centered on i (Geurs and Ritsema van Eck, 2001).

Consequently, we propose a third index which is a generalized and modified version of the Joseph and Bantock indicator. It introduces an imputed job-search intensity correction that affects both the relevant labor supply and demand according to the following formula:

$$A_3^i = \sum_{j=1}^{N} p_{ij} \frac{E_j}{\sum\limits_{k=1}^{N} p_{kj} R_k} \tag{7}$$

with

$$p_{ij} = \frac{f(d_{ij})\, E_j}{\sum\limits_{j=1}^{N} f(d_{ij})\, E_j} \tag{8}$$

where p_{ij} is the fraction of time that individual i devotes to search in location j (we have $\sum\limits_{j=1}^{N} p_{ij} = 1$). (8) assumes that workers search more in neighborhoods where jobs are concentrated. For each municipality, this index corresponds to a ratio of effective labor demand and labor supply assuming that workers search only within a 45-minute isochron of their residence and that they spend proportionally more time searching in places where jobs are more numerous.

These indices can be calculated for each transport mode (since the 45-minute isochrons differ). For private transport, they are highly correlated, the correlation between A_1 and A_2 (resp. A_1 and A_3, and A_2 and A_3) being .86 (resp. .88 and .86). For public transport, the correlations are lower. For A_1 and A_2 (resp. A_1 and A_3, and A_2 and A_3), the correlation is .31 (resp. .21 and .31).

8 Appendix B: the sensitivity analysis

The estimation of parameters is conducted using maximum likelihood. For any given individual i, the probabilities in this appendix are conditional on the set of observed explanatory variables in the transition and location equations. To make notations simple, this conditioning is omitted. In the likelihood, the contribution of a given individual depends on his number of transitions. When an individual only experiences one transition at date t_0, his contribution writes:

$$P_i = P\left(E_{it_0} = e_0, L_i = j\right)$$

where e_0 is the observed exit. When an individual experiences two transitions at dates t_0 and t_{0+1}, his contribution writes:

$$P_i = P\left(E_{it_0} = e_0, E_{it_0+1} = e_1, L_i = j\right)$$

where e_0 and e_1 are the observed exits at dates t_0 and t_{0+1}.

The log-likelihood writes $\Lambda = \sum_i \ln P_i$. It can be decomposed as $\Lambda = \Lambda_L + \Lambda_{E|L}$ where Λ_L is the log-likelihood of location:

$$\Lambda_L = \sum_i \ln P\left(L_i = j\right)$$

and $\Lambda_{E|L}$ is the log-likelihood of exit conditionally on location:

$$\Lambda_{E|L} = \sum_{i\in\Phi} \ln P\left(E_{it_0} = e_0 \left| L_i = j \right.\right) + \sum_{i\in\Psi} \ln P\left(E_{it_0} = e_0, E_{it_0+1} = e_1, \left| L_i = j \right.\right)$$

where Φ is the set of individuals experiencing one transition only and Ψ is the set of individuals experiencing two transitions.

The log-likelihood of location Λ_L is very easy to compute. The individual contribution to the conditional log-likelihood $\Lambda_{E|L}$ can be computed by generalizing the calculations in Rosenbaum and Rubin (1983). Calculations are detailed below in subsection 8.1. As the number of locations is small ($J = 8$) compared to the number of observations, it is possible to estimate the coefficients of all observed variables in the location equations. We maximize the full likelihood Λ with respect to $\alpha = (\alpha_2, ..., \alpha_E)$, $\beta = (\beta_2, ..., \beta_E)$, $\lambda = (\lambda_2, ..., \lambda_J)$ and θ.

8.1 Calculation of the log-likelihood

The calculation of the likelihood depends on the law of the unobserved individual variable. In the location log-likelihood Λ_L, the contribution of individual i writes:

$$P\left(L_i = j\right) = E_{u_i}\left[P\left(L_i = j \left| u_i \right.\right)\right] \tag{9}$$

with:

$$P\left(L_i = j \left| u_i \right.\right) = \frac{\exp(A_{it_0}\lambda_j + B_{jt_0}\theta + \delta_j u_i)}{1 + \sum_\ell \exp(A_{it_0}\lambda_\ell + B_{\ell t_0}\theta + \delta_\ell u_i)} \tag{10}$$

If individual i experiences one transition only, his contribution to the conditional likelihood $\Lambda_{E|L}$ writes:

$$P\left(E_{it_0} = e_0 \left| L_i = j \right.\right) = E_{u_i|L_i=j}\left[P\left(E_{it_0} = e_0 \left| L_i = j, u_i \right.\right)\right] \tag{11}$$

If individual i experiences two transitions, using the fact that, conditionally on u_i, exits are independent, his contribution to the conditional likelihood $\Lambda_{E|L}$ writes:

$$P\left(E_{it_0} = e_0, E_{it_0+1} = e_1 \left| L_i = j \right.\right) = E_{u_i|L_i=j}\left[P\left(E_{it_0} = e_0 \left| L_i = j, u_i \right.\right) P\left(E_{it_0+1} = e_1 \left| L_i = j, u_i \right.\right)\right] \tag{12}$$

where:

$$P\left(E_{it} = e \left| L_i = j, u_i \right.\right) = \frac{\exp\left(X_{it}\alpha_e + Z_{jt}\beta_e + \gamma_e u_i\right)}{1 + \sum_{e>1} \exp\left(X_{it}\alpha_e + Z_{jt}\beta_e + \gamma_e u_i\right)} \tag{13}$$

Denote $f(.)$ the density of u_i and $f(. \left| L_i = j \right.)$ the density of u_i conditionally on location. Using the Bayes rule, we have:

$$f\left(u_i\left|L_i=j\right.\right)=\frac{P\left(L_i=j\left|u_i\right.\right)f\left(u_i\right)}{P\left(L_i=j\right)} \tag{14}$$

Plugging (9) and (10) into (14), we get a formula for $f\left(u_i\left|L_i=j\right.\right)$ that only depends on observed explanatory variables and parameters. Using this formula as well as (13), and (11) or (12), we obtain the contribution of individual i to the conditional likelihood.

In practice, following the literature (Rosenbaum and Rubin, 1983) we assume that u_i simply follows a Bernoulli law, taking two values, a_1 and a_2, with respective probabilities π_1 and π_2. We can then simplify the expressions. In the location likelihood Λ_L, the contribution of individual i writes:

$$P\left(L_i=j\right)=\sum_{k=1}^{2}\pi_k P\left(L_i=j\left|u_i=a_k\right.\right) \tag{15}$$

with:

$$P\left(L_i=j\left|u_i=a_k\right.\right)=\frac{\exp(A_{it_0}\lambda_j+B_{jt_0}\theta+\delta_j a_k)}{1+\sum\limits_{\ell}\exp(A_{it_0}\lambda_\ell+B_{\ell t_0}\theta+\delta_\ell a_k)} \tag{16}$$

If individual i experiences one transition only, his contribution to the conditional likelihood $\Lambda_{E|L}$ writes:

$$P\left(E_{it_0}=e_0\left|L_i=j\right.\right)=\sum_{k=1}^{2}P\left(E_{it_0}=e_0\left|L_i=j,u_i=a_k\right.\right)P\left(u_i=a_k\left|L_i=j\right.\right) \tag{17}$$

If individual i experiences two transitions, his contribution to the conditional likelihood $\Lambda_{E|L}$ writes:

$$\begin{aligned}&P\left(E_{it_0}=e_0,E_{it_0+1}=e_1\left|L_i=j\right.\right)\\=&\sum_{k=1}^{2}P\left(E_{it_0}=e_0\left|L_i=j,u_i=a_k\right.\right)P\left(E_{it_0+1}=e_1\left|L_i=j,u_i=a_k\right.\right)P\left(u_i=a_k\left|L_i=j\right.\right)\end{aligned} \tag{18}$$

The probability that individual i experiences an exit of type e conditionally on the unobserved individual variable is given by:

$$P\left(E_{it}=e\left|L_i=j,u_i=a_k\right.\right)=\frac{\exp\left(X_{it}\alpha_e+Z_{jt}\beta_e+\gamma_e a_k\right)}{1+\sum\limits_{e>1}\exp\left(X_{it}\alpha_e+Z_{jt}\beta_e+\gamma_e a_k\right)} \tag{19}$$

Using the Bayes rule, we get for any k:

$$P\left(u_i=a_k\left|L_i=j\right.\right)=\frac{P\left(u_i=a_k\right)P\left(L_i=j\left|u_i=a_k\right.\right)}{P\left(L_i=j\right)} \tag{20}$$

Using equations (20), (15), (19), and (17) or (18), we obtain the contribution of individual i to the conditional likelihood.

8.2 Application

We apply the methodology to the specification of labor-market transitions that uses seven dummies for the HAC clusters ($J=8$).

We assume that u_i is a binary variable that is drawn in the set $\{-1/2, 1/2\}$ with a probability equal to 1/2 for each value. In A_i, we include a constant and dummies for gender, age and age^2, diploma, and nationality. We do not include any local variable in B_j since the values would not vary much across individuals (as there are only eight clusters).
We test the robustness of the results on four sets of $S = 1,000$ simulations for the effects of individual unobserved heterogeneity. In the first set, the coefficients of the unobserved variable (γ_e and δ_j) are drawn in the uniform law on $[-\ln 2; \ln 2]$ ensuring that the corresponding *odds-ratios* are comprised between 1/2 and 2. In the second, third, and four sets of simulations, they are drawn in the uniform laws on $[-\ln 3; \ln 3]$, $[-\ln 4; \ln 4]$ and $[-\ln 5; \ln 5]$ respectively. The coefficients for the transition and location of reference are always set at 0 ($\delta_0 = 0$ and $\gamma_0 = 0$).

Simulation results for odds-ratios in $[-1/2, 1/2]$ (γ_e and δ_j drawn in $[-\ln 2; \ln 2]$) are reported in Tables $A2$ to $A4$.Graph 1 represents the descriptive statistics on the sign and significance of the coefficient of the type-III cluster for each labor-market transition. Graph 2 plots the same information for the type-V cluster. Both graphs are discussed in the main body of the text.

[*Insert Tables* $A2$ *to* $A4$]

9 Appendix C: Alternative specifications

We ran alternative specifications of equation (2).[20]

First, we discretized the segregation and job-accessibility variables in order to detect potential non-linearities. For each contextual variable, we created dummies for quartiles and re-ran the regression with those dummies. The are three noticeable differences with the main regression. The municipality proportion of Africans is not significant anymore. There is a non-linearity effect for the job-density by public transport: the third quartile has a significant negative effect on finding a job (the reference being the first quartile) but the fourth quartile has no effect. For the job density by private transport, the fourth quartile has a significant positive effect on the premature exit from the panel.

Second, we changed the geographic scale of the segregation variables:

- When the proportion of educated workers in the neighborhood is replaced by the same proportion but at the municipality level, none of the segregation variables has a significant effect on finding a job and prematurely exiting the panel. Both variables have a negative significant effect on dropping out of the labor force. These results could be explained by the negative correlation between the proportion of Africans and educated workers at the municipality level.
- Conversely, when the proportion of Africans is measured at the neighborhood level rather than at the municipality level, we obtain the same result for finding a job except that the negative effect of job density by

[20] Details are available upon request.

public transport is now significant at a 5% level (instead of 10%). For the premature exit from the panel, the proportion of Africans still has a negative effect but it becomes non-significant. For dropping out of the labor force, job density by public transport has a negative effect that is now significant at 10%.

- When the proportion of educated workers is at the municipality level and the proportion of Africans is at the neighborhood level, for finding a job, the signs of the contextual effects remain the same. However, the effect of the proportion of educated workers is not significant anymore. For prematurely exiting from the panel, the signs are also unchanged but the proportion of Africans does not have a significant effect anymore.

Third, we also considered other segregation variables:

- When the neighborhood proportion of educated workers is replaced by the neighborhood proportion of high-skilled white collars, we find very similar results. This is not surprising since the two variables are highly correlated. For finding a job, the neighborhood proportion of high-skilled white collars has a positive effect that is significant at 10%. The job density by public transport still has a negative effect that is significant at 10%. For the premature exit from the panel, the neighborhood proportion of high-skilled white collars still has a positive effect but it is not significant. The municipality proportion of Africans has a negative effect which becomes significant at 5%.

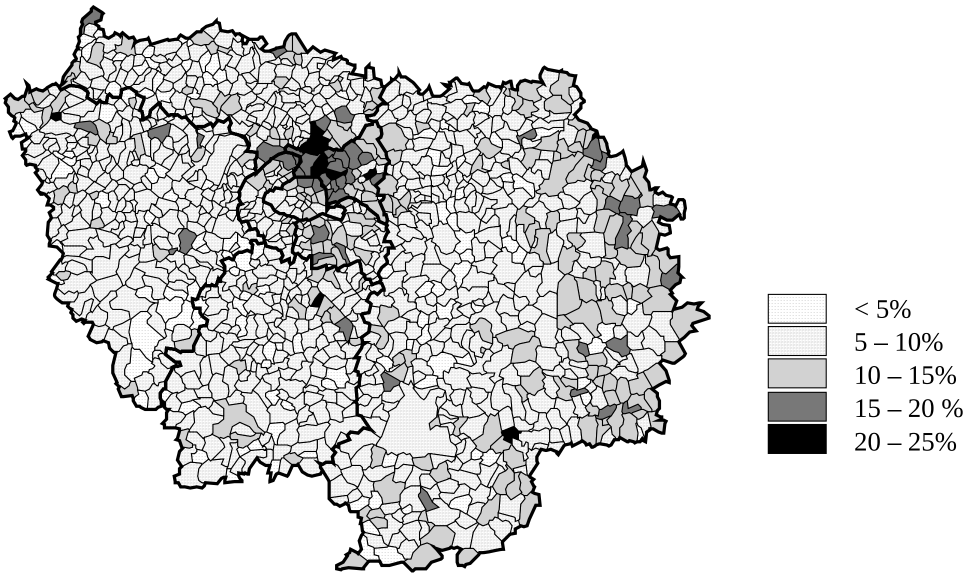
- When the neighborhood proportion of educated workers is replaced by the neighborhood proportion of unemployed and out-of-the-labor-force residents, the latter has a negative effect on finding a job that is significant at 1%.[21] This result is consistent with Dujardin, Selod and Thomas (2004) on Brussels who show that the local unemployment rate has a positive effect the unemployment probability of young adults living with their parents. Job density by public transport does not have a significant effect anymore. For the premature exit from the panel, the municipality proportion of Africans has a negative effect which becomes significant at 5%. The job density by private transport has a positive effect which becomes significant at 10%. The proportion of unemployed and out-of-the-labor-force neighbors has a negative effect but it is not significant even at the 10% level.

Fourth, we used the alternative job-accessibility indices described in appendix A. When we use the measure A_2, results remain the same for segregation variables. The negative effect of job accessibility by private transport on finding a job becomes significant at the 10% level. When we use the measure A_3, the municipality proportion of Africans still has negative effects on all exits which become significant at the 5% level except for dropping out of the labour which is significant at 10%. Once again, the negative effect of job accessibility by private transport on finding a job becomes significant at the 10% level.

[21] One should be cautious when interpreting this result. Indeed, the effect can be due to the weakness of social interactions or to redlining. It can also be generated by some local unobservables that would simultaneously explain the local unemployment rate and the local constraints impeding unemployed workers from finding a job.

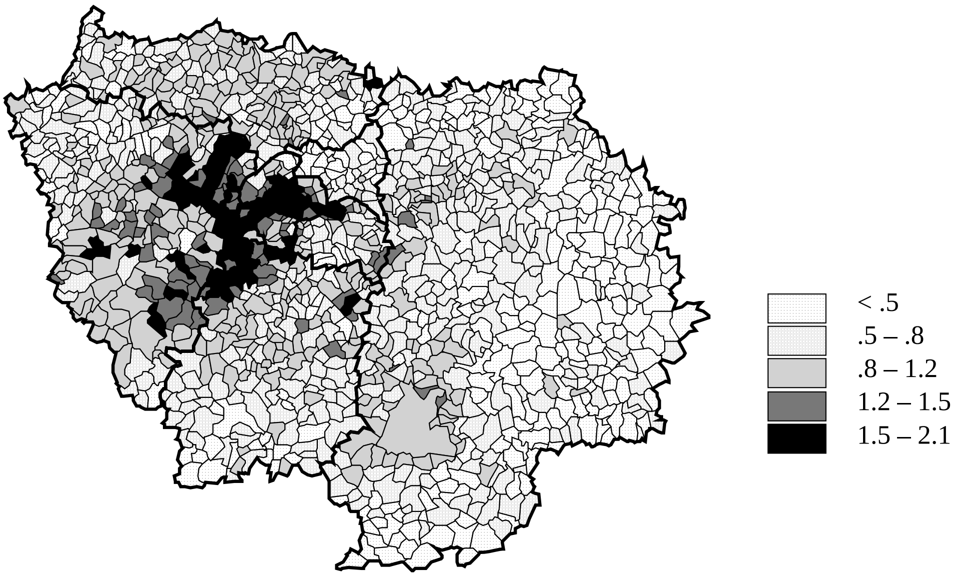
Fifth, we also computed job densities separately by educational level. In the regression, we crossed a dummy for each educational level (with *vs* without a high school diploma) with the corresponding job-density and with the segregation variables. For finding a job, we find that only the low-educated are positively affected by the neighborhood level of education. The low-educated are the only ones to be negatively affected (at the 10% level) by their job accessibility.

Map 1. Municipality unemployment rates in the Paris region



Source: Census of the Population (1999), INSEE.
Note: Geographical units are municipalities. The thick lines are the borders of the region's districts (*départements*). The city of Paris is at the center. Clockwise around Paris are the Hauts-de-Seine (west), the Seine-Saint-Denis (north east) and the Val-de-Marne (south east). The peripheral districts are the Yvelines (west), the Val d'Oise (north), the Seine-et-Marne (east), and the Essonne (south).

Map 2. Specialization index for educated workers (at the municipality level)



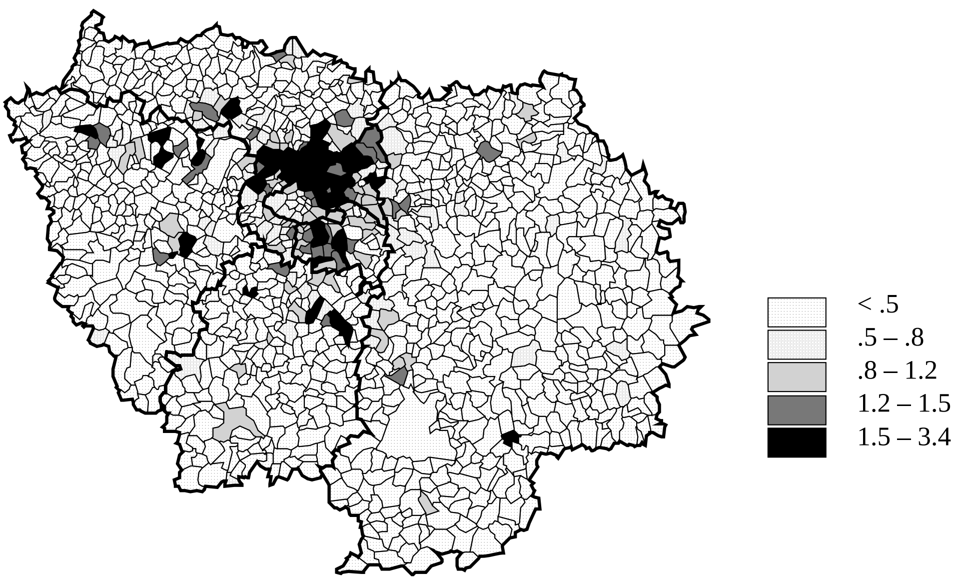
Source: Census of the Population (1999), INSEE.
Note: Educated workers have a high school diploma or above.

Table 1. Residential segregation indexes

	Paris region	City of Paris	Inner ring	Outer ring
Inter-municipality segregation indexes				
Unemployed / occupied workers	.16	.12	.17	.15
Skilled white collars / clerks	.26	.14	.26	.21
Skilled white collars / blue collars	.39	.23	.38	.32
Blue collars / clerks	.15	.10	.14	.13
Educated workers (high school diploma) / Low-educated workers	.25	.15	.23	.19
French / Maghrebines	.32	.21	.27	.39
French / Africans (excl. Maghrebines)	.32	.23	.25	.39
Africans (excl. Maghrebines) / Maghrebines	.13	.05	.12	.19

Source: Census of the Population (1999), INSEE.
Note: The indexes are Duncan and Duncan (1955) computed on a spatial breakdown with municipalities as geographical units.

Map 3. Residential specialization index for Africans (at the municipality level)



Source: Census of the Population (1999), INSEE.

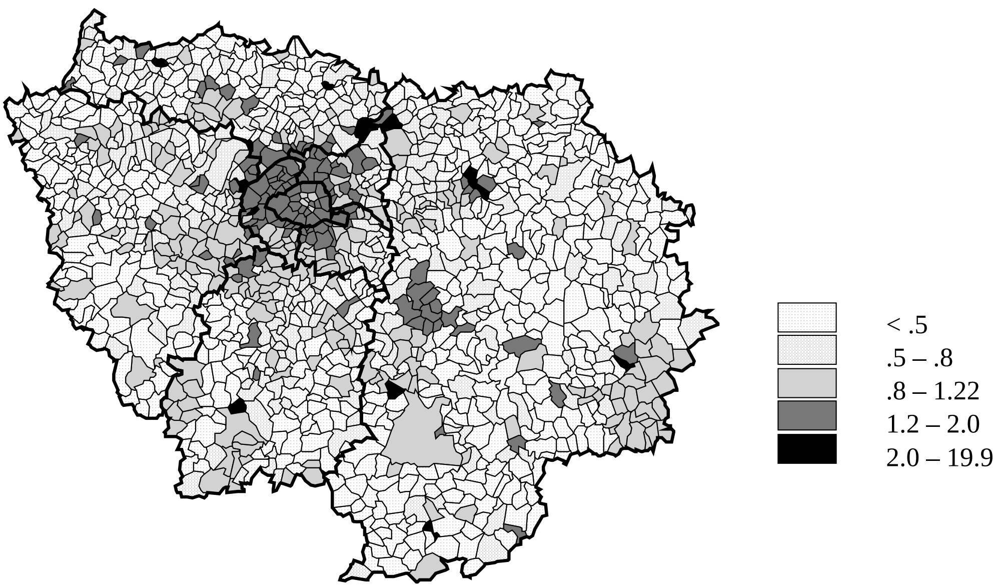
Table 2. Job disconnection and accessibility measures

	Paris region	City of Paris	Inner ring	Outer ring
Inter-municipality job-disconnection indexes				
Labor force / jobs	.25	.22	.20	.25
Skilled white collars / corresponding jobs	.31	.23	.30	.39
Clerks / corresponding jobs	.30	.27	.21	.26
Blue collars / corresponding jobs	.25	.24	.18	.25
Educated workers (high-school diploma or above) / corresponding jobs	.26	.21	.24	.30
Low-educated workers (without high school diploma) / corresponding jobs	.26	.26	.19	.23
French / jobs held by French workers	.26	.22	.22	.27
Maghrebines / jobs held by Maghrebine workers	.25	.25	.17	.27
Africans (excl. Maghrebines) / jobs held by African (excl. Maghrebines) workers	.33	.32	.25	.30
Average job-density within 45 minutes				
By public transport				
All	1.06	1.30	1.22	.81
High-school diploma	1.07	1.21	1.20	.85
Without high-school diploma	1.05	1.44	1.26	.77
By private transport				
All	.86	1.03	.87	.76
High-school diploma	.91	1.05	.91	.81
Without high-school diploma	.80	1.00	.83	.72

Sources: Census of the Population (1999), INSEE, and General Transport Survey (2000), DREIF.

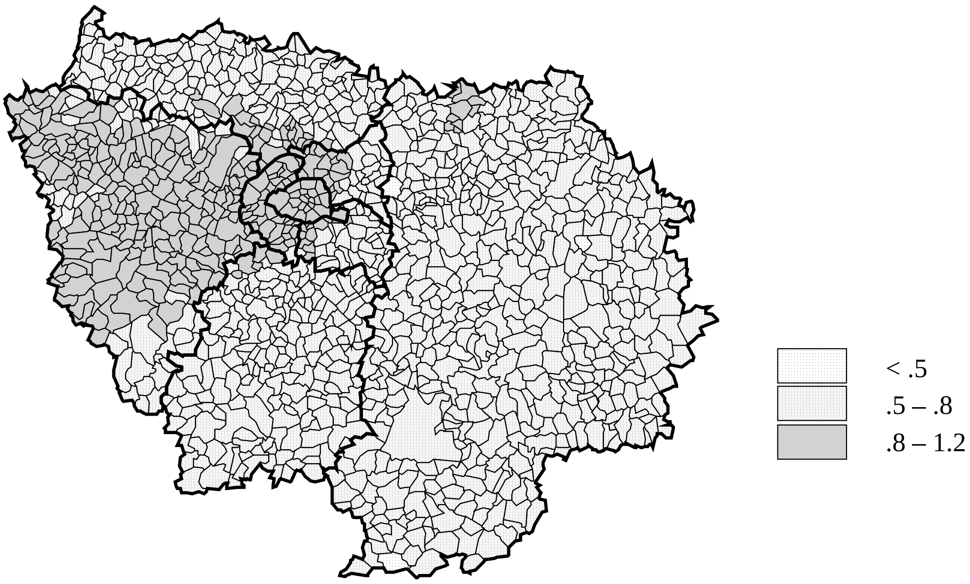
Notes: Duncan and Duncan (1955) indexes are computed on a municipality spatial breakdown. Averages are calculated weighting by the labor force in each municipality.

Map 4. Job densities within 45 minutes by public transport (centered on each municipality)



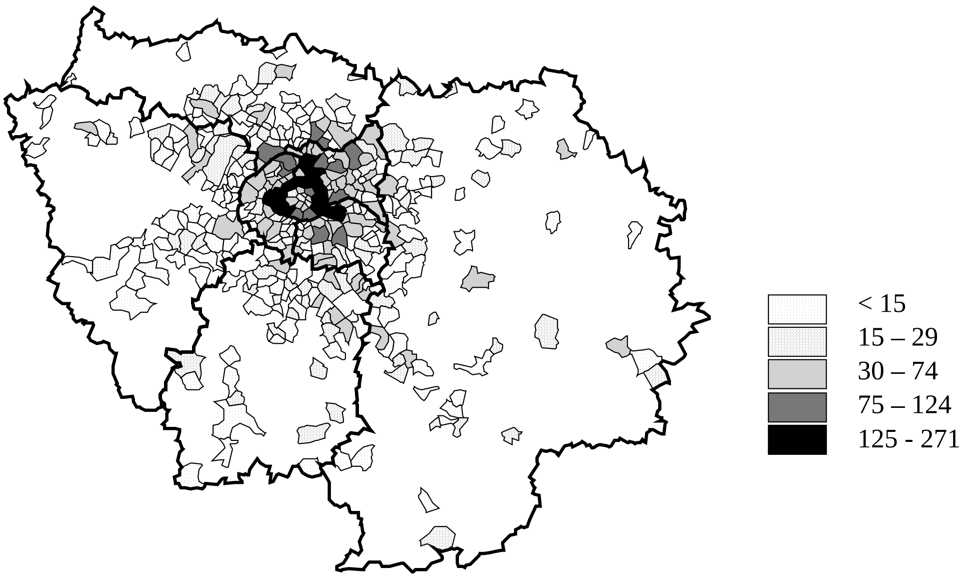
Sources: Census of the Population (1999), INSEE, and General Transport Survey (2000), DREIF.

Map 5. Job densities within 45 minutes by private transport (centered on each municipality)



Sources: Census of the Population (1999), INSEE, and General Transport Survey (2000), DREIF.

Map 6. Number of observed labor-market transitions in the 1990-2002 Labor Force Survey



Source: Labor Force Survey (1990-2002), INSEE
Note: A municipality may host several neighborhoods.

Table 3. Descriptive statistics on neighborhoods-years (1990-2002 LFS)

	Average	Std dev	Min	Max	1st decile	9th decile
Totals						
Number of people	27.0	15.1	1	109	12	48
Number of workers in the labor force	21.8	12.2	1	89	10	38
Number of unemployed or out-of-the-labor-force individuals	7.8	5.2	1	49	2	15
Number of unemployed workers	2.5	1.9	1	18	1	5
Percentages						
% unemployed or out-of-the-labor-force individuals	.29	.13	.04	1.00	.14	.46
% unemployed workers	.13	.10	.01	1.00	.05	.25
% skilled white collars	.21	.20	.00	1.00	.00	.50
% educated (high school diploma)	.41	.24	.00	1.00	.13	.75
% Africans	.07	.12	.00	1.00	.00	.23

Source: Labor Force Survey (1990-2002), INSEE.
Note: There are 3,905 observations of the neighborhood-year type for which labor-market transitions starting during the 1990-2001 period are observed. Averages are weighted by the number of transitions.

Table 4. Correlation matrix between neighborhood and municipality variables

	Neighborhoods				Municipalities					
	% skilled white collars	% educated workers	% Africans (including Maghrebines)	% out-of-the-labor-force or unemployed workers	% skilled white collars	% educated workes	% Africans (including Maghrebines)	% unemployed workers	Job density within 45 minutes (private vehicules)	Job density within 45 minutes (public transport)
Neighborhoods										
% skilled white collar neighbors	1.00									
%educated neighbors	.82	1.00								
% African neighbors	-.35	-.34	1.00							
% out-of-the-labor-force or unemployed neighbors	-.28	-.30	.46	1.00						
Municipalities										
% skilled white collars in the municipality	.60	.63	-.22	-.22	1.00					
% educated workers in the municipality	.60	.63	-.21	-.27	.98	1.00				
% Africans in the municipality	-.32	-.27	.48	.23	-.47	-.46	1.00			
% unemployed workers in the municipality	-.36	-.33	.42	.36	-.58	-.56	.90	1.00		
Job density within 45 minutes (private transport)	.39	.41	.07	-.02	.60	.60	.17	.03	1.00	
Job density within 45 minutes (public transport)	.20	.23	.13	.05	.32	.32	.32	.23	.64	1.00

Sources: Labor Force Survey (1999-2002) and Census of the Population (1999), INSEE, and General Transport Survey (2000), DREIF.

Note: Statistics are computed by weighting by the number of transitions in each neighborhood-area. All correlations are significant at the 1% level.

Table 5a. The Hierachical Ascending Classifications of neighborhoods

	Neighborhood segregation		Municipality segregation		Job accessibility	
	strong	weak	strong	weak	bad	good
Neighborhood characteristics % educated neighbors	26.4	63.3				
% African neighbors	11.7	1.3				
Municipality characteristics % educated in municipality			34.5	50.8		
% Africans in municipality			12.8	4.5		
Job-accessibility indexes Job density within 45 minutes (public)					.88	1.38
Job density within 45 minutes (private)					.77	1.02
Totals Number of areas	1,457	1,639	1,402	1,694	1,660	1,436
Number of areas with transitions	1,264	1,160	1,157	1,267	1,346	1,078
Number of transitions	6,520	3,120	5,448	4,192	5,074	3,566

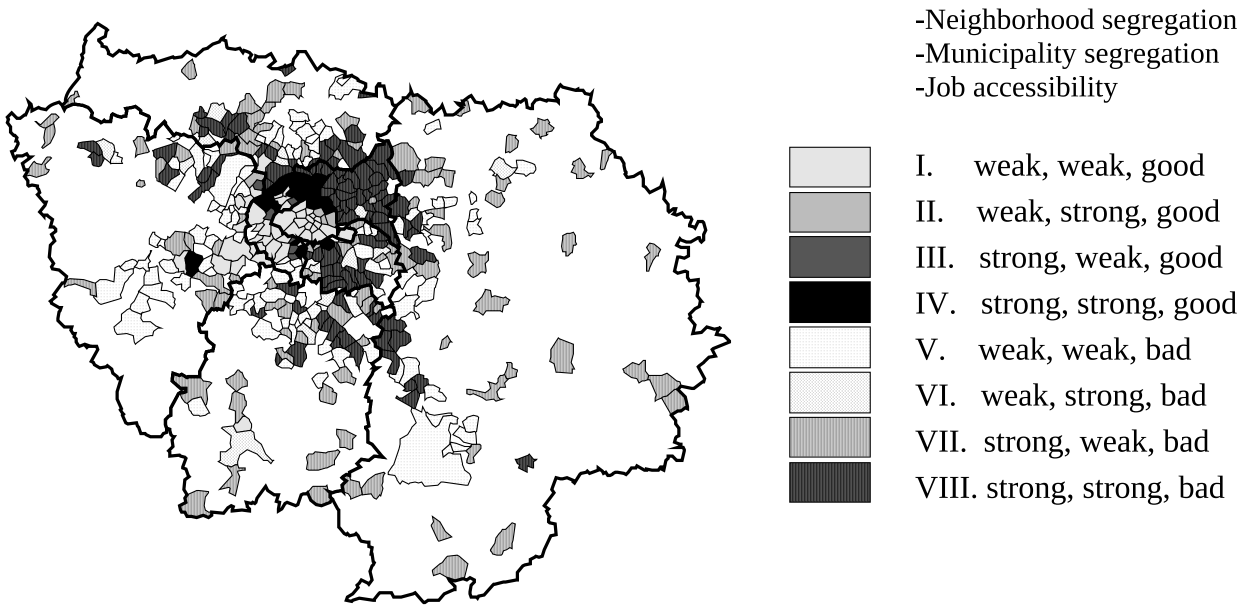
Sources: Labor Force Survey (1999-2002), Census of the Population (1999), INSEE, and General Transport Survey (2000), DREIF.

Table 5b. The eight-class typology of neighborhoods

	I	II	III	IV	V	VI	VII	VIII
Class characteristics								
Neighborhood segregation	weak	weak	**strong**	**strong**	weak	weak	**strong**	**strong**
Municipality segregation	weak	**strong**	weak	**strong**	weak	**strong**	weak	**strong**
Job accessibility	good	good	good	good	**bad**	**bad**	**bad**	**bad**
Neighborhood characteristics								
% educated neighbors	70.8	64.9	34.6	29.9	56.2	52.7	23.7	23.7
% African neighbors	1.7	1.8	12.3	18.2	.4	1.0	5.3	12.3
Municipality characteristics								
% educated in municipality	60.6	45.3	55.8	39.7	44.6	32.5	36.1	28.5
% Africans in municipality	5.3	12.8	5.9	15.0	3.5	10.5	3.4	12.6
Job-accessibility indexes								
Job accessibility (public)	1.39	1.35	1.44	1.36	.83	.92	.74	.98
Job accessibility (private)	1.03	1.00	1.04	.99	.79	.76	.74	.76
Totals								
Number of areas	704	253	196	283	442	240	352	626
Number of areas with transitions	490	182	159	247	311	177	307	551
Number of transitions	1,266	501	547	1,252	829	524	1,550	3,171

Sources: Labor Force Survey (1999-2002), Census of the Population (1999), INSEE, and General Transport Survey (2000), DREIF.
Note: “Weak segregation” corresponds to a high proportion of educated workers and a low proportion of Africans.

Map 7. Main neighborhood type in the municipality



Sources: Labor Force Survey (1999-2002), Census of the Population (1999), INSEE, and General Transport Survey (2000), DREIF.
Note: The baseline neighborhoods (type I) are characterized by weak levels of segregation both at the neighborhood and municipality scales as well as a good job accessibility.

Table 6a. Results of the regression with segregation and job-accessibility measures

	Finding a job without moving		Dropping out of the labor force without moving		Leaving the panel (move or no answer)	
	Coeff. (Std dev)	Odds-ratio	Coeff. (Std dev)	Odds-ratio	Coeff. (Std dev)	Odds-ratio
Age/10	.394** (.189)	1.483	-1.830*** (.208)	.160	-.756*** (.185)	.470
(Age/10) squared	-.096*** (.025)	.909	.253*** (.026)	1.288	.046* (.024)	1.047
Gender: Female	-.097* (.055)	.908	.699*** (.069)	2.011	-.015 (.055)	.985
Education						
No diploma or professional certificate (CEP)	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
Technical diploma (below high school diploma)	.200*** (.071)	1.221	-.065 (.089)	.937	.058 (.073)	1.059
Technical high school diploma	.648*** (.145)	1.912	.023 (.202)	1.024	.274* (.156)	1.316
General high school diploma	-.313*** (.119)	.731	-.084 (.151)	.920	-.075 (.115)	.927
University degree	.441*** (.082)	1.554	.121 (.107)	1.129	.350*** (.083)	1.419
Nationality						
French	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
European (other)	.227** (.111)	1.255	.029 (.141)	1.029	.155 (.114)	1.168
Maghrebine	-.175* (.100)	.839	.067 (.115)	1.069	.002 (.095)	1.002
African (other)	-.258* (.147)	.773	.145 (.174)	1.156	.104 (.134)	1.109
Other nationality	-.228 (.141)	.796	-.057 (.172)	.945	-.068 (.134)	.934
Search method						
National Employment Agency (ANPE) only	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
National Employment Agency (ANPE) and other methods	.313*** (.111)	1.367	-.693*** (.103)	.500	-.130 (.101)	.878
Without National Employment Agency (ANPE)	.637*** (.136)	1.892	.199 (.133)	1.221	.241* (.127)	1.272
Housing occupancy status						
Owner	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
Renter of the public sector (HLM)	-.041 (.076)	.959	.165* (.093)	1.180	.398*** (.081)	1.489
Renter of the private sector or free occupation	.002 (.071)	1.002	-.053 (.091)	.948	.715*** (.074)	2.044
% neighbors with high school diploma	.356** (.162)	1.427	-.268 (.202)	.765	.454*** (.160)	1.575
% Africans in the municipality	-.690 (.522)	.501	-.827 (.646)	.438	-.936* (.524)	.392
Job density within 45 minutes (public transport)	-.169* (.097)	.845	-.161 (.121)	.851	-.073 (.101)	.929
Job density within 45 minutes (private transport)	-.254 (.259)	.776	-.034 (.317)	.967	.283 (.263)	1.327

Sources: Labor Force Survey (1999-2002), Census of the Population (1999), INSEE, and General Transport Survey (2000), DREIF.
Note: Number of observations: 9,640. *** significance at the 1% level; ** 5%, * 10% .
We included a constant term and year fixed effects. The coefficients are not reported in the table.

Table 6b. Results of the regression with dummies for neighborhood type

	Finding a job without moving		Dropping out of the labor force without moving		Leaving the panel (move or no answer)	
	Coeff. (Std dev)	Odds-ratio	Coeff. (Std dev)	Odds-ratio	Coeff. (Std dev)	Odds-ratio
Age/10	.399** (.189)	1.490	-1.829*** (.208)	.161	-.737*** (.185)	.479
(Age/10) squared	-.096*** (.025)	.908	.253*** (.026)	1.288	.043* (.024)	1.044
Gender: Female	-.099* (.055)	.906	.691*** (.069)	1.996	-.014 (.055)	.986
Education						
No diploma or professional certificate (CEP)	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
Technical diploma (below high school diploma)	.207*** (.071)	1.230	-.067 (.089)	.935	.062 (.073)	1.064
Technical high school diploma	.615*** (.146)	1.850	.008 (.202)	1.008	.237 (.157)	1.267
General high school diploma	-.333*** (.119)	.717	-.093 (.151)	.911	-.101 (.115)	.904
University degree	.454*** (.083)	1.575	.111 (.107)	1.117	.378*** (.083)	1.459
Nationality						
French	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
European (other)	.219** (.111)	1.245	.032 (.141)	1.033	.154 (.114)	1.166
Maghrebine	-.195* (.100)	.823	.062 (.115)	1.064	-.009 (.095)	.991
African (other)	-.276* (.148)	.759	.129 (.174)	1.138	.091 (.134)	1.095
Other nationality	-.240 (.141)	.787	-.058 (.172)	.944	-.077 (.134)	.926
Search method						
National Employment Agency (ANPE) only	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
National Employment Agency (ANPE) and other methods	.303*** (.111)	1.354	-.695*** (.103)	.499	-.144 (.101)	.866
Without National Employment Agency (ANPE)	.638*** (.136)	1.893	.210 (.133)	1.234	.233* (.127)	1.262
Housing occupancy status						
Owner	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
Renter of the public sector (HLM)	-.041 (.075)	.960	.221** (.091)	1.247	.414*** (.081)	1.513
Renter of the private sector or free occupation	.020 (.072)	1.020	-.023 (.091)	.977	.742*** (.075)	2.100
Neighborhood type						
Type I	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
Type II	-.231 (.143)	.794	-.091 (.186)	.913	-.158 (.137)	.854
Type III	-.341** (.149)	.711	.011 (.178)	1.011	-.103 (.135)	.902
Type IV	-.042 (.115)	.959	.062 (.148)	1.064	-.098 (.111)	.907
Type V	.338*** (.124)	1.402	.394** (.157)	1.483	.234* (.126)	1.264
Type VI	.277** (.141)	1.319	.333 (.183)	1.395	.169 (.145)	1.184
Type VII	.030 (.110)	1.030	.285** (.139)	1.330	-.185* (.111)	.831
Type VIII	-.086 (.102)	.918	.140 (.131)	1.150	-.309*** (.101)	.734

Sources: Labor Force Survey (1999-2002), Census of the Population (1999), INSEE, and General Transport Survey (2000), DREIF.
Note: Number of observations: 9,640. *** significance at the 1% level; ** 5%, * 10% .
We included a constant term and year fixed effects. The coefficients are not reported in the table.

Table 7a. Results of the regression for the sub-sample of workers residing in public housing, with segregation and job-accessibility measures

	Finding a job without moving		**Dropping out of the labor force without moving**		**Leaving the panel (move or no answer)**	
	Coeff. (Std dev)	Odds-ratio	Coeff. (Std dev)	Coeff. (Std dev)	Odds-ratio	Coeff. (Std dev)
Age/10	.422 (.331)	1.525	-1.705*** (.337)	.182	-.499 (.323)	.607
(Age/10) squared	-.095** (.045)	.909	.226*** (.043)	1.254	.010 (.043)	1.010
Gender: Female	.001 (.097)	1.001	.718*** (.116)	2.051	.080 (.098)	1.083
Education						
No diploma or professional certificate (CEP)	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
Technical diploma (below high school diploma)	.133 (.118)	1.142	-.115 (.144)	.891	.076 (.121)	1.079
Technical high school diploma	.513 (.348)	1.670	.202 (.432)	1.224	.681** (.334)	1.976
General high school diploma	-.330 (.274)	.719	-.030 (.325)	.970	-.329 (.267)	.719
University degree	.498** (.196)	1.646	.245 (.241)	1.278	.634*** (.194)	1.885
Nationality						
French	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
European (other)	.007 (.245)	1.007	.163 (.271)	1.177	.279 (.237)	1.322
Maghrebine	-.119 (.145)	.888	.192 (.157)	1.212	-.036 (.147)	.965
African (other)	-.212 (.212)	.809	-.242 (.263)	.785	-.407* (.231)	.666
Other nationality	-.088 (.271)	.916	.063 (.295)	1.065	-.070 (.273)	.932
Search method						
National Employment Agency (ANPE) only	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
National Employment Agency (ANPE) and other methods	.599*** (.191)	1.820	-.565*** (.164)	.569	-.271* (.156)	.763
Without National Employment Agency (ANPE)	.871*** (.250)	2.390	.250 (.230)	1.283	-.113 (.229)	.893
% neighbors with high school diploma	.777** (.377)	2.175	.115 (.444)	1.122	.837** (.374)	2.308
% Africans in the municipality	-.505 (.897)	.604	-.660 (1.053)	.517	-2.221** (.907)	.108
Job density within 45 minutes (public transport)	-.260 (.199)	.771	.071 (.234)	1.073	-.250 (.202)	.779
Job density within 45 minutes (private transport)	.330 (.496)	1.390	-.110 (.571)	.896	1.187** (.493)	3.276

Sources: Labor Force Survey (1999-2002), Census of the Population (1999), INSEE, and General Transport Survey (2000), DREIF.
Note: Number of observations: 3,108. *** significance at the 1% level; ** 5%, * 10% .
We included a constant term and year fixed effects. The coefficients are not reported in the table.

Table 7b. Results of the regression for the sub-sample of workers residing in public housing, with dummies for neighborhood type

	Finding a job without moving		Dropping out of the labor force without moving		Leaving the panel (move or no answer)	
	Coeff. (Std dev)	Odds-ratio	Coeff. (Std dev)	Coeff. (Std dev)	Odds-ratio	Coeff. (Std dev)
Age/10	.442 (.331)	1.556	-1.694*** (.336)	.184	-.445 (.323)	.641
(Age/10) squared	-.098** (.045)	.907	.226*** (.043)	1.254	.004 (.044)	1.004
Gender: Female	-.004 (.097)	.996	.718*** (.116)	2.050	.088 (.098)	1.092
Education						
No diploma or professional certificate (CEP)	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
Technical diploma (below high school diploma)	.135 (.118)	1.145	-.119 (.144)	.888	.092 (.121)	1.096
Technical high school diploma	.471 (.349)	1.602	.199 (.433)	1.220	.629* (.334)	1.876
General high school diploma	-.343 (.276)	.710	-.026 (.327)	.974	-.327 (.269)	.721
University degree	.558*** (.198)	1.747	.246 (.245)	1.279	.679*** (.196)	1.972
Nationality						
French	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
European (other)	-.001 (.245)	.999	.139 (.271)	1.149	.274 (.237)	1.315
Maghrebine	-.226 (.145)	.798	.191 (.157)	1.210	-.041 (.146)	.960
African (other)	-.217 (.211)	.805	-.236 (.262)	.790	-.423* (.231)	.655
Other nationality	-.084 (.271)	.919	.047 (.295)	1.048	-.075 (.272)	.928
Search method						
National Employment Agency (ANPE) only	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
National Employment Agency (ANPE) and other methods	.599*** (.191)	1.820	-.573*** (.164)	.564	-.276* (.156)	.759
Without National Employment Agency (ANPE)	.885*** (.250)	2.423	.251 (.230)	1.285	-.097 (.228)	.908
Neighborhood type						
Type I	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
Type II	-.702 (.559)	.496	-.498 (.789)	.608	-.816 (.611)	.442
Type III	-.436 (.418)	.647	-.462 (.474)	.630	-.477 (.379)	.621
Type IV	-.268 (.386)	.765	-.346 (.439)	.708	-.786** (.357)	.456
Type V	.361 (.588)	1.435	-.091 (.713)	.913	.119 (.551)	1.126
Type VI	.020 (.538)	1.020	.066 (.602)	1.068	-.580 (.526)	.560
Type VII	-.173 (.382)	.841	-.191 (.436)	.826	-.641* (.353)	.527
Type VIII	-.314 (.372)	.731	-.278 (.424)	.757	-.877** (.342)	.416

Sources: Labor Force Survey (1999-2002), Census of the Population (1999), INSEE, and General Transport Survey (2000), DREIF.
Note: Number of observations: 3,108. *** significance at the 1% level; ** 5%, * 10% .
We included a constant term and year fixed effects. The coefficients are not reported in the table.

Table A1. Results of the location model

Neighborhood type	II	III	IV	V	VI	VII	VIII
Constant	-1.478*	1.734**	1.777***	1.317**	-.569	1.975***	3.008***
	(.788)	(.681)	(.569)	(.599)	(.729)	(.535)	(.495)
Age	.368	-.968***	-.358	-.705**	.028	-.313	-.395
	(.411)	(.364)	(.309)	(.326)	(.397)	(.291)	(.268)
Age²	-.049	.100**	.006	.081**	-.015	.006	-.003
	(.051)	(.046)	(.039)	(.041)	(.051)	(.037)	(.034)
Female	.019	-.088	.052	.139	.202*	.155*	.114
	(.117)	(.116)	(.093)	(.099)	(.117)	(.089)	(.080)
Technical diploma (below high school diploma)	.382**	.204	-.239*	.249	.453**	.214	-.083
	(.188)	(.166)	(.142)	(.157)	(.175)	(.131)	(.125)
Technical high school diploma	-.211	-.921***	-1.222***	.442*	.364	-.665***	-1.118***
	(.344)	(.350)	(.279)	(.232)	(.267)	(.228)	(.222)
General high school diploma	-.180	.335	.494***	.127	.682***	.542***	.879***
	(.195)	(.227)	(.178)	(.165)	(.191)	(.192)	(.147)
University degree	-.282**	-1.643***	-2.137***	-.785***	-1.112***	-2.558***	-2.673***
	(.144)	(.156)	(.126)	(.125)	(.156)	(.131)	(.110)
European (other)	-.068	-.465*	-.134	-.462**	-.153	-.570***	-.028
	(.230)	(.258)	(.181)	(.207)	(.235)	(.180)	(.152)
Maghrebine	.585*	1.902***	2.212***	-.609	.298	.888***	1.822***
	(.328)	(.255)	(.228)	(.386)	(.345)	(.242)	(.221)
African (other)	-.017	2.024***	2.293***	-.516	1.018***	.985***	1.899***
	(.531)	(.333)	(.291)	(.528)	(.392)	(.316)	(.277)
Other nationality	.271	.428*	.398*	-.965***	.334	-.891***	.272
	(.249)	(.258)	(.209)	(.314)	(.251)	(.264)	(.179)

Sources: Labor Force Survey (1999-2002), Census of the Population (1999), INSEE, and General Transport Survey (2000), DREIF.
Note: Number of observations: 9,640. *** significance at the 1% level; ** 5%, * 10% .

Table A2. Results of the sensitivity analysis for the modality "finding a job", with dummies for neighborhood type

	% <0	**% <0 ns**	**% >0 ns**	**% >0**	**Min**	**1st dec.**	**Med.**	**9nt dec.**	**Max**
Age/10	.000	.000	.000	1.000	.391	.401	.408	.418	.434
(Age/10) Squared	1.000	.000	.000	.000	-.101	-.099	-.098	-.097	-.096
Gender: Female	.000	1.000	.000	.000	-.106	-.103	-.100	-.098	-.096
Education									
No diploma or professional certificate (CEP)	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
Technical diploma (below high school diploma)	.000	.000	.000	1.000	.203	.207	.209	.212	.216
Technical high school diploma	.000	.000	.000	1.000	.607	.616	.620	.626	.637
General high school diploma	1.000	.000	.000	.000	-.348	-.340	-.336	-.332	-.327
University degree	.000	.000	.000	1.000	.439	.452	.457	.462	.476
Nationality									
French	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
European (other)	.000	.000	.929	.071	.210	.216	.219	.222	.227
Maghrebinee	.445	.555	.000	.000	-.217	-.202	-.196	-.191	-.176
African (other)	.013	.987	.000	.000	-.302	-.285	-.278	-.273	-.255
Other nationality	.000	1.000	.000	.000	-.254	-.245	-.241	-.238	-.231
Search method									
National Employment Agency (ANPE) only	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
National Employment Agency (ANPE) and other methods	.000	.000	.000	1.000	.301	.304	.307	.311	.318
Without National Employment Agency (ANPE)	.000	.000	.000	1.000	.636	.638	.640	.644	.649
Housing occupancy status									
Owner	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
Renter of the public sector (HLM)	.000	1.000	.000	.000	-.049	-.045	-.042	-.040	-.038
Renter of the private sector or free occupation	.000	.000	1.000	.000	.004	.013	.017	.021	.024
Neighbordhood type									
Type I (reference)	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
Type II	.133	.867	.000	.000	-.370	-.287	-.230	-.175	-.100
Type III	.858	.142	.000	.000	-.520	-.410	-.339	-.287	-.171
Type IV	.000	.848	.152	.000	-.218	-.102	-.041	.012	.096
Type V	.000	.000	.020	.980	.184	.288	.341	.393	.483
Type VI	.000	.000	.450	.550	.089	.220	.279	.333	.416
Type VII	.000	.216	.784	.000	-.118	-.025	.033	.086	.185
Type VIII	.001	.989	.010	.000	-.210	-.133	-.086	-.043	.020

Sources: Labor Force Survey (1999-2002), Census of the Population (1999), INSEE, and General Transport Survey (2000), DREIF.
Note: Statistics are computed on 1.000 simulations. The first four columns respectively provide the percentage of negative coefficients significant at the 5% level, negative not significant at 5%, positive not significant at 5%, and positive significant at 5%.

Table A3. Results of the sensitivity analysis for the modality "dropping out of the labor force", with dummies for neighborhood type

	% <0	% <0 ns	% >0 ns	% >0	Min	1^{st} dec.	Med.	9^{nt} dec.	Max
Age/10	1.000	.000	.000	.000	-1.861	-1.847	-1.838	-1.832	-1.826
(Age/10) Squared	.000	.000	.000	1.000	.253	.254	.255	.256	.258
Gender: Female	.000	.000	.000	1.000	.691	.694	.696	.700	.705
Education									
No diploma or professional certificate (CEP)	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
Technical diploma (below high school diploma)	.000	1.000	.000	.000	-.076	-.071	-.068	-.065	-.059
Technical high school diploma	.000	.994	.006	.000	-.027	-.017	-.011	-.005	.010
General high school diploma	.000	1.000	.000	.000	-.102	-.097	-.093	-.089	-.082
University degree	.000	.000	1.000	.000	.093	.106	.111	.116	.131
Nationality									
French	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
European (other)	.000	.000	1.000	.000	.021	.027	.031	.034	.040
Maghrebinee	.000	.000	1.000	.000	.042	.057	.062	.068	.083
African (other)	.000	.000	1.000	.000	.109	.122	.129	.136	.150
Other nationality	.000	1.000	.000	.000	-.085	-.073	-.068	-.064	-.056
Search method									
National Employment Agency (ANPE) only	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
National Employment Agency (ANPE) and other methods	1.000	.000	.000	.000	-.710	-.704	-.699	-.697	-.694
Without National Employment Agency (ANPE)	.000	.000	1.000	.000	.202	.206	.209	.211	.213
Housing occupancy status									
Owner	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
Renter of the public sector (HLM)	.000	.000	.000	1.000	.218	.220	.222	.225	.229
Renter of the private sector or free occupation	.000	1.000	.000	.000	-.031	-.027	-.024	-.021	-.016
Neighbordhood type									
Type I (reference)	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
Type II	.000	.975	.025	.000	-.276	-.145	-.088	-.032	.078
Type III	.000	.347	.653	.000	-.151	-.046	.013	.071	.176
Type IV	.000	.101	.899	.000	-.122	.000	.064	.120	.238
Type V	.000	.000	.053	.947	.220	.337	.397	.445	.546
Type VI	.000	.000	.664	.336	.165	.275	.340	.392	.492
Type VII	.000	.000	.343	.657	.127	.226	.287	.345	.416
Type VIII	.000	.000	.999	.001	.011	.096	.142	.188	.269

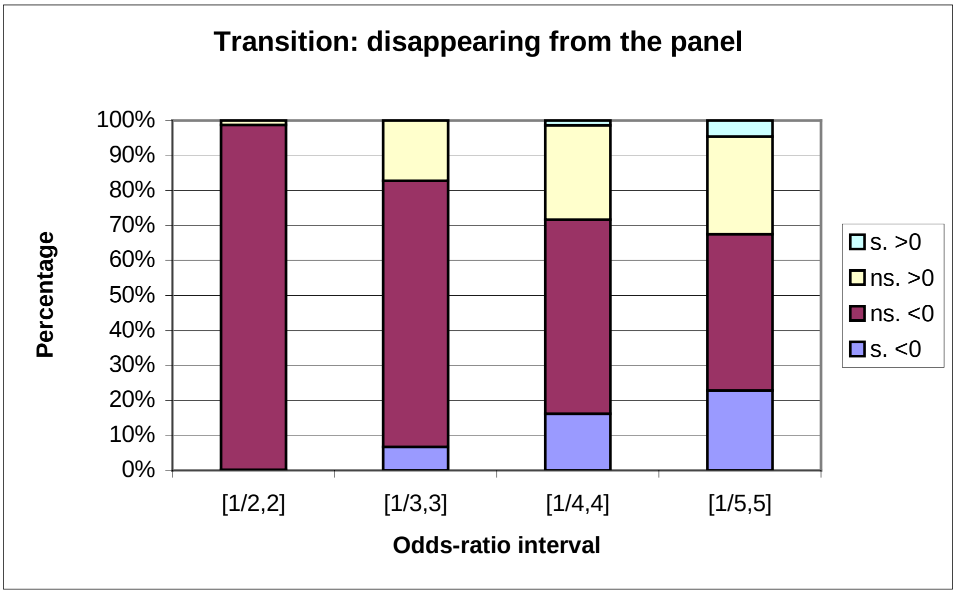
Sources: Labor Force Survey (1999-2002), Census of the Population (1999), INSEE, and General Transport Survey (2000), DREIF.
Note: Statistics are computed on 1.000 simulations. The first four columns respectively provide the percentage of negative coefficients significant at the 5% level, negative not significant at 5%, positive not significant at 5%, and positive significant at 5%.

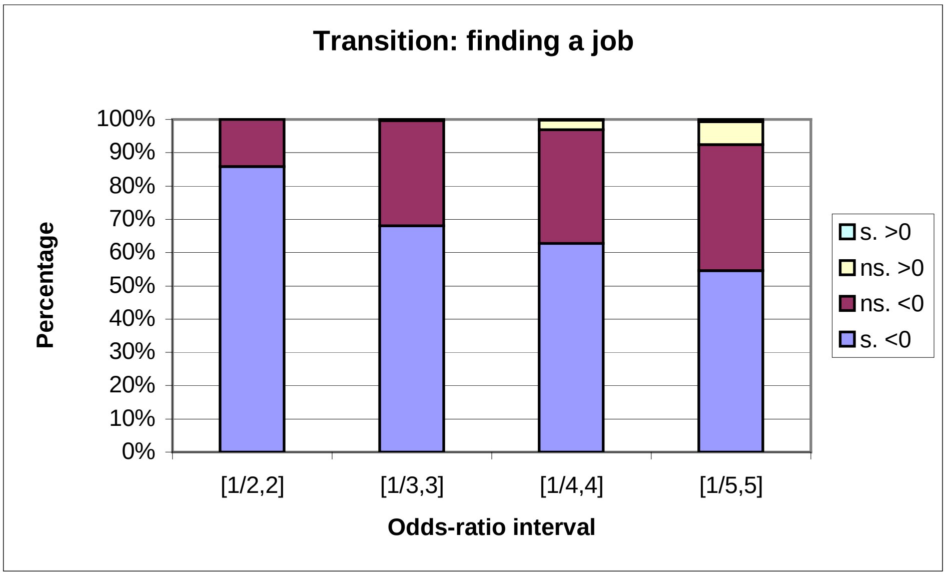
Table A4. Results of the sensitivity analysis for the modality “prematurely leaving the panel”, with dummies for neighborhood type

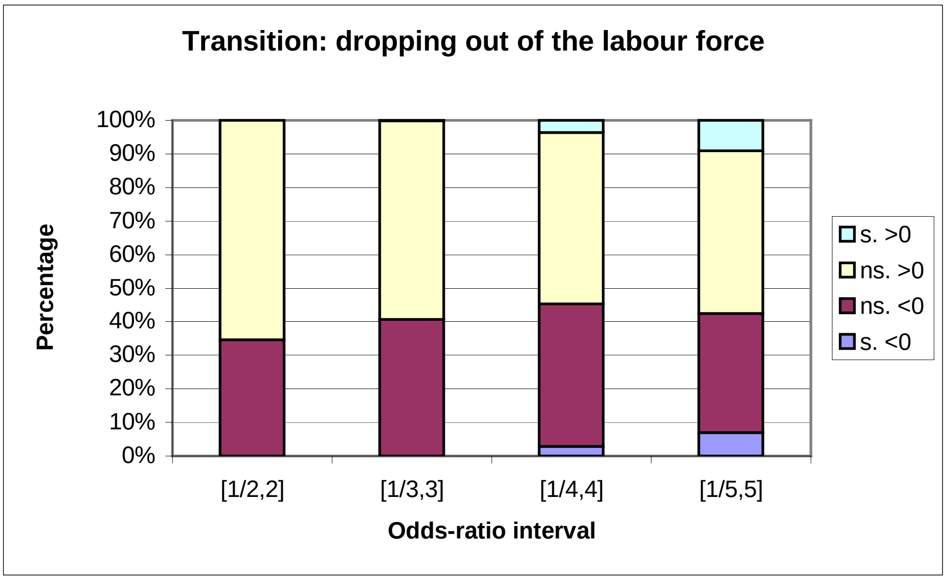
	% <0	% <0 ns	% >0 ns	% >0	Min	1^{st} dec.	Med.	9^{nt} dec.	Max
Age/10	1.000	.000	.000	.000	-.763	-.750	-.741	-.733	-.725
(Age/10) squared	.000	.000	1.000	.000	.041	.043	.044	.045	.047
Gender: Female	.000	1.000	.000	.000	-.023	-.017	-.015	-.013	-.010
Education									
No diploma or professional certificate (CEP)	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
Technical diploma (below high school diploma)	.000	.000	1.000	.000	.053	.059	.062	.064	.067
Technical high school diploma	.000	.000	1.000	.000	.217	.232	.237	.242	.251
General high school diploma	.000	1.000	.000	.000	-.111	-.104	-.100	-.097	-.090
University degree	.000	.000	.000	1.000	.354	.375	.380	.385	.401
Nationality									
French	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
European (other)	.000	.000	1.000	.000	.148	.152	.155	.158	.163
Maghrebine	.000	.966	.034	.000	-.029	-.014	-.010	-.004	.012
African (other)	.000	.000	1.000	.000	.075	.086	.092	.098	.116
Other nationality	.000	1.000	.000	.000	-.087	-.079	-.076	-.072	-.065
Search method									
National Employment Agency (ANPE) only	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
National Employment Agency (ANPE) and other methods	.000	1.000	.000	.000	-.153	-.148	-.145	-.142	-.134
Without National Employment Agency (ANPE)	.000	.000	1.000	.000	.225	.230	.232	.234	.239
Housing occupancy status									
Owner	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
Renter of the public sector (HLM)	.000	.000	.000	1.000	.412	.414	.416	.419	.425
Renter of the private sector or free occupation	.000	.000	.000	1.000	.743	.745	.748	.752	.757
Neighbordhood type									
Type I (reference)	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>	<Ref.>
Type II	.014	.985	.001	.000	-.319	-.213	-.156	-.102	.005
Type III	.001	.987	.012	.000	-.294	-.162	-.100	-.049	.029
Type IV	.005	.985	.010	.000	-.250	-.153	-.097	-.046	.054
Type V	.000	.000	.620	.380	.061	.175	.235	.286	.379
Type VI	.000	.000	.995	.005	.028	.110	.171	.227	.328
Type VII	.223	.777	.000	.000	-.334	-.246	-.184	-.137	-.051
Type VIII	.996	.004	.000	.000	-.453	-.364	-.310	-.271	-.183

Sources: Labor Force Survey (1999-2002), Census of the Population (1999), INSEE, and General Transport Survey (2000), DREIF.
Note: Statistics are computed on 1.000 simulations. The first four columns respectively provide the percentage of negative coefficients significant at the 5% level, negative not significant at 5%, positive not significant at 5%, and positive significant at 5%.

Graph 1. Sign and significance of the effects of living in a type-III neighborhood on labor-market transitions (under increasing degrees of endogeneity)

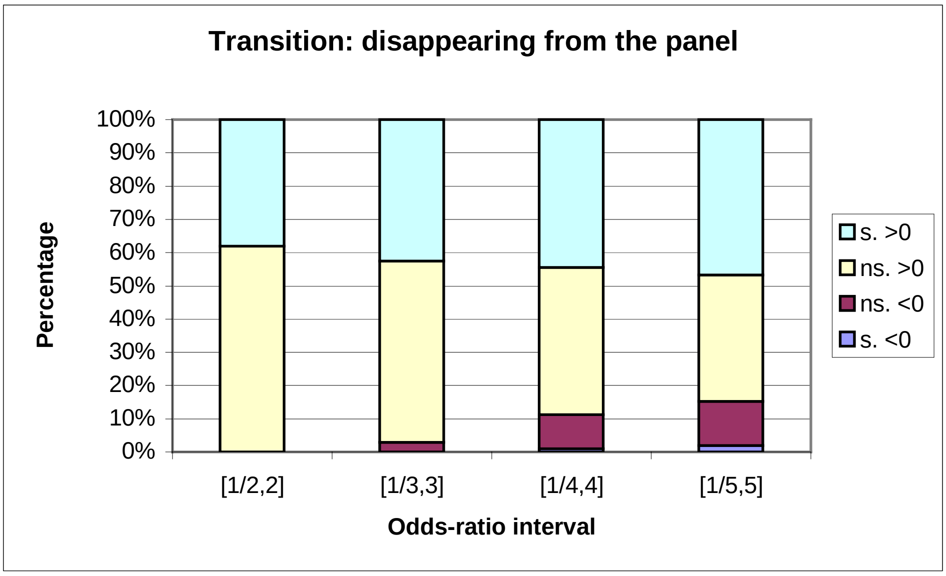


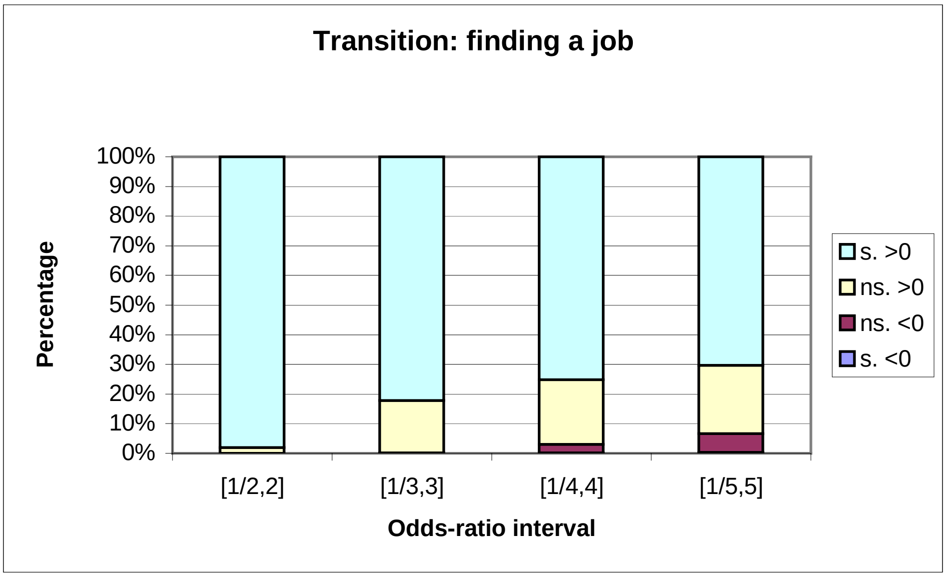


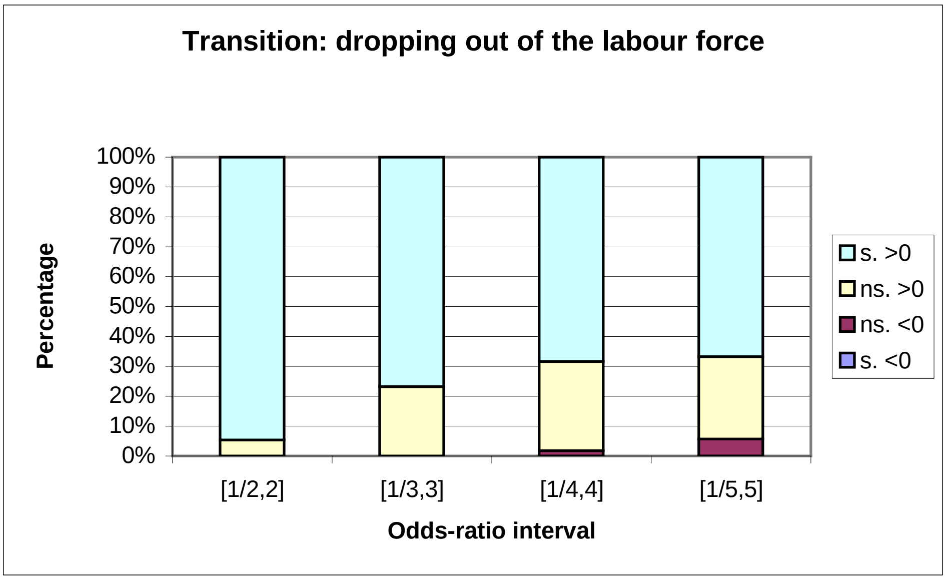


s: significant at the 5% level. Ns: not significant at the 5% level.

Graph 2. Sign and significance of the effects of living in a type-V neighborhood on labor-market transitions (under increasing degrees of endogeneity)







s: significant at the 5% level. Ns: not significant at the 5% level.