Urban segregation and labour markets within the Bordeaux metropolitan area: an investigation of the spatial friction

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Abstract: This article aims at providing a test of the spatial mismatch hypothesis on the Bordeaux metropolitan area. Starting with a theoretical survey of the complex links between residential segregation and local labour markets, we then propose a framework allowing for a better understanding of the impact of physical distance on spatial mismatch. The results confirm the existence of two different effects of spatial friction depending on the distance considered. Furthermore, the results provide some evidence of the existence of a spatial hysteresis effect affecting specifically long-term unemployment.

Key words: *residential segregation, spatial mismatch hypothesis, unemployment..*

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INTRODUCTION

In order to deal with urban unemployment and especially high unemployment rates neighbourhoods, urban welfare policy makers have for a long time been waving between "people" and "place" options (Kain, 1968). The defenders of the people option generally argue that distressed neighbourhoods are simply the consequence of an insufficient labour demand at the metropolitan scale combining with residential segregation to adversely affect the neighbourhoods where the local labour force exhibits low-employability characteristics (Cheschire, 1981). Such a diagnostic leads to policies aiming at enhancing the employability of local job seekers as well as increasing the metropolitan labour demand.

The tenants of the place option point out that residential segregation and discrimination in the housing market can prevent job seekers from accessing to the job opportunities offered within the metropolitan labour market. This hypothesis leads to the identification of a specific neighbourhood effect by which the employment probabilities of job seekers can be adversely affected not only by their own socio-economic characteristics but also by the nature of the neighbourhood where they live. The most widely accepted hypothesis to explain such neighbourhoods effects is known as the "spatial mismatch hypothesis". This hypothesis, initially enunciated by John Kain in 1968, was that discrimination against minorities in the suburban housing market combined with the employment suburbanisation process have caused growing unemployment and/or decreasing earnings for those "trapped" in inner cities, and especially blacks. Although formulated in the specific north–American context, it was widely disseminated around the world. For example, the spatial mismatch hypothesis has made up the main theoretical framework of the "inner areas studies" conducted in Great Britain during the seventies (Cheschire, 1979).

As it was intensely used, the hypothesis gets a broader sense. A contemporaneous definition could be that residential segregation and jobless neighbourhoods combine to adversely affect the employment opportunities of people living in high unemployment districts. Also broadly defined and widely discussed, and in spite of the important work on this subject during last decades, there is still little consensus about its empirical validity as well as its theoretical foundations, as stressed in two recent surveys (Ihlanfeld and Sojkist, 1998; Kain, 1998).

This paper has thus three main purposes. Firstly, we will propose a typology of the possible theoretical links between residential segregation and urban unemployment, arguing that the spatial mismatch is only one possible interaction among others between residential segregation and local labour markets. It is thus important to distinguish clearly the spatial mismatch effect from other explanations, such as labour force composition or negative neighbourhood externalities. Otherwise, the effect of physical access to job opportunities could result in an overestimation of the spatial mismatch effect.

We then propose a framework allowing for such identification, using a set of data on the Bordeaux metropolitan area, with some specific features. Notably, most of precedent studies used the total number of jobs as a proxy for job opportunities. As the correlation is not necessarily high, we use directly data about employment offers (extracted from the French National Agency for Employment (ANPE) files).

Thirdly, we propose a range of tests with varying distance to discuss the effect of distance on the intensity of the spatial mismatch. In most previous studies, distance is arbitrarily defined and the authors surprisingly do not discuss its impact on spatial friction.

I- THE THEORETICAL AND METHODOLOGICAL FUNDATIONS OF THE SPATIAL MISMATCH HYPOTHESIS

The abundance of applied studies has given contrast for a long time with the absence of inquiry of possible theoretical foundations of subjacent mechanisms to SMH (Kain, 1992). However, a number of recent studies have attempted to reduce this gap through the providing of a theoretical framework linking residential segregation and local labour markets (Gaschet, 1998; Gobillon et al., 2002).

I-1 Theoretical foundations

The SMH links, in its more generic version, two very different kinds of phenomena: in one hand, the mechanisms of residential segregation; in the other hand, the different kinds of friction of space involved in the job-matching process. Instead of an exhaustive survey of the theoretical work on this subject (see, for exemple, Gobillon, Sélod and Zenou, 2002), we propose here a typology of what can be considered as the three main possible links between residential location and employment outcomes: A pure segregation effect (1), A spatial and/or mobility mismatch effect (2) and a spatial hysteresis mechanism (3).

I-1.1 The pure segregation effect

The literature in urban economics identifies three main reasons to explain the formation of segregate cities.

(i) The first one is directly tied to the traditional monocentric model of the New Urban Economics (Fujita, 1989). Considering a population of households with heterogeneous income competing for the occupation of urban land results traditionally in a income based-stratification of the urban space according to the distance to the city centre. Two opposing forces are identified. First, rich households have a high opportunity cost of time and are thus attracted by the accessibility to the city centre. However, as the housing consumption increases with income, rich people are attracted by low prices in the suburbs. The location of richest households thus depends on the evolution of the ratio of the commuting cost to land consumption with income, which can be consistent with a variety of location patterns. More recently, some authors have proposed an amenity-based theory that ties location by income to city's specific amenities pattern. These amenities can be located in the city centre (Brueckner, Thisse and Zenou, 1999) as well as at the urban fringe (Cavailhés et al., 2003).

(ii) The second main approach of urban segregation ties the concentration of low incomes households in some areas to the existence of neighbourhood externalities (Schelling, 1978; Bénabou, 1993). As a consequence of the preference of households for living in relative homogeneous neighbourhoods in terms of income or ethnic origin, people can run away from some central neighbourhoods to more homogeneous suburbs, thus initiating some self-reinforcing mechanisms, as suggested by the « flight from blight hypothesis» (Mieszkowsky and Mills, 1993; Mills and Lubuele, 1997).

(iii) Thirdly, the occurrence of segregation can be related to housing policies, such as the low apartment's rents programs intended for low income households. Evidence suggests that these programs are concentrated in some specific areas, whereas the relatively decentralized structure of local governments within cities tends to generate a kind of NIMBY syndrome. The effects of urban zoning and minimum lot size rules must also be emphasised (Duranton, 1997).

Taking into account these mechanisms of residential segregation leads to the conclusion that the pattern of unemployment rates within a city can be the result of some important variations in the characteristics of the resident labour force, such as age, lack of skill, family size…. As a result of residential segregation, the spatial variations in the variables that are known to have an influence on the employability of the labour force, such as age or skill, can explain the occurrence of high unemployment rates in some urban areas. In further analysis, we will refer to it as the *labour force's composition effect*.

I-1.2 The accessibility to job opportunities as a determinant of employment rates

Residential segregation can also lead to some restrictions to the mobility of residents, and especially less-skilled workers. The restricted mobility of segregate people is expected to make their job-search success or unemployment duration sensitive to local market conditions, and thus to some "spatial frictions".

This hypothesis, known as the spatial mismatch hypothesis, is grounded on three arguments related to increasing commuting costs (1), job-search costs (2) and the spatial segmentation of metropolitan labour markets (3)

(i) Prohibitive commuting costs

The basic theoretical argument is that more expensive commutes can increase the reservation wages of spatially isolated workers, causing them to forego employment, especially if employers refuse to compensate for it (Brueckner and Martin, 1997). As a result, the employment probabilities of workers who are constrained by segregation mechanisms to live in spatially isolated neighbourhoods should be lower than those of otherwise identical workers not similarly constrained, as Kain has pointed out initially concerning minorities living within inner cities (Kain, 1968; O'reagan and Quigley, 1998)

The impact of spatial isolation can be amplified by a restricted access of segregate populations to transportations facilities as well as by a default of car ownership. Taylor and Ong (1995) bring into contrast *spatial mismatch* and *automobile mismatch*, pointing out that the real problem lies into the availability of a car and/or public transportation rather than the labour demand conditions near the residence's place. Some comparable results have been obtained for the Lyon Metropolitan area (Mignot et al., 2001; Aguilera and Mignot, 2002). *A contrario,* using a simulation model, Martin (2001, p1317) concludes that "policies that are aimed at ensuring the access of low-income households to residential areas near to areas of employment growth would be more effective in neutralising spatial mismatch than commuting subsidies"

(ii) Spatial friction and job-search

W. Simpson (1982, 1992) provides a theoretical treatment of the link between information seeking involved in job search and the spatial mismatch. He asserts that metropolitan areas consist of a series of “islands”, with commuting and information seeking about jobs opportunities being free within islands but costly among islands. The model is grounded on the well known job-search theory, and considers only the frictional component of unemployment resulting from the trade off between the prospecting duration and the wage proposed.

Assuming that all workers prefer the local labour market of their place of residence, when local labour market demand is low, job seekers increase their prospective duration in order to prospect non local markets, and to compensate for higher commuting and search costs. Unemployment rates will thus tend to increase within low- labour demand “islands”.

As a consequence of job search theory and the increasing sparseness of suitable job opportunities across islands with increasing skills, the higher-skilled workers are assumed to adopt a more formal and spatially extended job-search strategy. Thus, the spatial mismatch should primarily affect low-skilled workers.

The above-mean dependence of low-skilled job seekers to local labour markets conditions could also be explained by the more informal information and job-search strategies used by these workers to find a job. When the more formal prospects strategies cannot be easily substituted to the more informal ones, the lack of job opportunities carried through local networks grounded on local social interactions could explain the employment drawbacks of some neighbourhoods (O’Reagan, Quigley, 1998).

(iii) Spatial segmentation of metropolitan labour markets and filtering process

Boyle (1998) assumes that in a metropolitan economy two very distinct labour markets coexist, a regional labour market and a local-neighbourhood labour market, each with its specific dynamics. The regional/metropolitan labour market, dynamic and offered to high-skill workers, can compete with the local markets more closed and within which job seekers use more informal information and social networks.

Two types of mechanisms are involved in this spatial segmentation:

- Firstly, a positive labour demand shock in a particular place may lead to this demand being satisfied mainly by long distance migrants at the expense of unemployed populations closer to the location of job offers. This can be called an eviction effect[2].
- Secondly, when employed people in the local markets cannot access to the larger range of opportunities in the regional market, (they are not filtering to better jobs), the traditional clearing process in the local labour markets breaks down, since the unemployed cannot obtain the local employment opportunities that would match theirs skills. This could be called a captivity effect.

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[2] BARTIK (1991) has calculated that, in the case of Chicago, 78% of the job growth goes to « immigrants » at the expense of local unemployed population.

I-1.3 Segregation and spatial hysteresis

Residential segregation can also be at the origin of a spatial hysteresis mechanism. Strictly defined, the spatial hysteresis hypothesis means that the concentration and the social isolation of low-income or low-skilled populations in some specific neighbourhoods can adversely affect their future ability to obtain employment, whatever their initial socio-economic characteristics of their physical accessibility to job opportunities.

The basic mechanism involved in the spatial hysteresis hypothesis is a combination of local negative externalities among jobless or low-income people within some neighbourhoods. Four explanations derived from the economic or sociological literature can be raised:

(i) Employers may discriminate against segregated workers because of their residential location (*redlining*) (Zenou and Boccard, 2000)

(ii) The negative influence of segregation on the educational attainments of young people, because of the peer effects (Arnott and Rowse, 1987 ; Benabou, 1993 ; Sélod, 2002).

(iii) The lack of density and/or diversity of the local social networks available for job seek (O'Reagan and Quigley, 1998)

(iv) The diffusion of deviant behaviours through local interactions, especially among young people, within deprived neighbourhoods, as suggested by the "epidemic" theory of ghettos proposed by Crane (1991).

The spatial hysteresis should be clearly distinguished from the pure segregation and spatial mismatch effects. Firstly, the SHH suggests that the employment probabilities of low-skilled people living in "ghettos" should be significantly lower than those of job seekers with the same skills but living in more diversified neighbourhoods, whereas the pure segregation effect would lead to similar employment probabilities. Secondly, these effects of the spatial concentration of low-income households are not tied to the accessibility to job opportunities. Thirdly, the SHH leads to a self-reinforcing mechanism supported by the different kinds of negative neighbourhood externalities involved.

Nevertheless, one can think that residential segregation or spatial mismatch can be at the origin of a spatial hysteresis process, then developing through its own dynamics.

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In further analysis, we will argue that a non-biased identification of the spatial mismatch effect requires taking into account three other possible explanations of intra-urban unemployment rates differentials: a pure segregation effect, an automobile mismatch effect and a spatial hysteresis mechanism.

I-2 Alternative tests of the spatial mismatch effect

Two main methodological approaches to empirically investigating the SMH have been proposed in the literature: (1) comparisons of commuting times or distance between social or racial groups; (2) correlation of unemployment or labour participation with some measures of job accessibility.

I-2.1 The inadequacy of the commuting times-based tests of the spatial mismatch hypothesis

Based on the seminal work of J. Kain, several studies have attempted to test the SMH assuming that households unable to reach more favourable residential locations because of segregation should have longer commuting times or distance than others.

Nevertheless, empirical results exhibit very contradictory conclusions. For example, Mc Lafferty and Preston (1996) as well as Gabriel and Rosenthal (1996) find a significant extension of commuting times of minorities whereas Gordon et al. (1989) and Taylor and Ong (1995) cannot detect any significant effect.

Ihlanfeld and Sojkist (1998) point out two possible sources of bias:

(i) The commuting length of households is highly correlated with their income, as stressed by the standard monocentric model.

(ii) Even in the presence of spatial mismatch, the unavailability of transportation facilities can prohibit the access to distant employment places.

But the more definitive criticism is due to DeRango (2001) who shows, using a simple simulation model, that spatial mismatch can produce even an extension or a contraction of commuting times or distances, depending on the evolution of the job opportunities' density with distance to the place of residence.

I-2.2 Direct access measures to job opportunities

The first generation of studies attempting to use indicators of accessibility to job opportunities suffer from drawbacks. Some of these studies used very rough indicators of the disequilibrium between the central city and the suburbs. In the same way, the use of distance-weighted measures of accessibility to jobs was unable to take into account the intensity of competition in the local labour market.

In the last generation of empirical studies, some authors have attempted to use the commuting times of employed workers of a neighbourhood as an indicator of the availability of jobs opportunities near their place of residence. This method, initiated by Ihlanfeld and Sojkist (1990), often leads to very significant results[3]. Nevertheless, it's subject to a number of criticisms. Firstly, the variations in commuting times among neighbourhoods underestimate the variations in accessibility to employment, since residents can be constraint in their spatial mobility. Secondly, this method compels to omit by construction the nature high- or less-skilled of the jobs, of which the distributions are not necessarily similar.

Following Ihlanfeldt and Sojkist (1998), a suitable measure of accessibility to job opportunities has to match three kinds of imperatives:

(i) Firstly, it has to take into account the local competition for job opportunities among the local labour force, through the use of jobs per resident ratios.

(ii) Secondly, it must consider the matching between the skill requirements of job offers ands the individual skills of job seekers.

[3] See the survey of Ihlanfeldt and Sojkist (1998).

(iii) Thirdly, it must use a direct measure of job opportunities instead of total employment or employment growth, insofar as these statistics are not necessarily correlated with the number of job offers during a year.

The work of Immergluck (1998) satisfies the two first criterions. He combines employment rates computed over very small areas units (neighbourhoods) with an indicator of employment accessibility (the number of jobs per resident) computed for each neighbourhood over a larger area of fixed radius. He is thus able to treat the jobs per resident ratio as an exogenous variable. Immergluck shows in his work on Chicago, that total employment accessible to residents has only a small effect on local employment rates. The influence becomes significant only when a favourable total employment combines with a high jobs-per-resident ratio and a good adequacy of jobs to local skills.

Nevertheless, the studies of Immergluck, as well as the one of Cooke (1996), do not match the third criterion. Using the employment growth as well as the total number of jobs, Raphaël (1998) and Rogers (1997) obtain results much more significant with the former, because of a seemingly better correlation with the number of job offers.

I-2-3 Exploring the spatial mismatch hypothesis with a varying distance

Considering the importance of the “friction of space” in the generic formulation of the spatial mismatch hypothesis, it’s surprising that, to our knowledge, there has been no attempt to explore the intensity of mismatch for different distances, or to appreciate at which distance the spatial friction matters. Some studies use spatial areas of accessibility to jobs identical to the residence areas (Gobillon and Sélod, 2002). Others use accessibility areas larger than those of residence, but with an arbitrary fixed radius, fixed at 2 miles in the study of Immergluck (1998). Even when using distance-weighted accessibility measures to jobs, the parameter describing the friction of distance remains fixed, like in Rogers (1997).

The question is not only empirical, but also of theoretical interest: the spatial friction implied by the assumed job search behaviour of low-skilled job seekers is not identical as the one implied by prohibitive commuting costs. One could think the latter to be higher than the former. Thus, the investigation of the spatial mismatch with varying distance could help to discriminate between alternative theoretical foundations of this hypothesis.

We will propose, in further analysis, a systematic exploration of the varying intensity of the spatial mismatch effect depending on the distance used to appreciate the accessibility to jobs.

II- A TEST OF THE SPATIAL MISMATCH HYPOTHESIS ON THE BORDEAUX METROPOLITAN AREA

An interesting case study to test the theoretical framework of the SMH is the Bordeaux metropolitan area. On one hand, recent studies have shown that it is a place where different spatial dynamics of job supply and demand come out (Gaussier, Lacour, Puissant, 2003). Job seekers are trapped in unemployment in some restricted areas that could be depicted as a “ghetto” effect, and analysed with commuting times to the city centre (Puissant, Gaussier, 2001). On the other hand, the empirical test of the SMH requires a set of specific spatial data we have at our disposal. We cross at the residential quarter level two French national sources of spatial data to investigate the main characteristics of the residents in the working population and to grasp directly at the quarter section level the employment offers.

II-1 Model and data

We present an explanatory model of the SMH that tend to enlighten the impact of distance on local unemployment rate (1). Then, we will expose the data sources we have used to define the exogenous variables and process to empirically investigating the SMH hypothesis (2).

II-1.1 Model development

The model aims at testing the local unemployment rate according to a vector of variables that explain the complex links between residential segregation and local labor markets. These links are drawn directly from the theoretical framework built in part I. They result in four possible explanations (or four possible sets of variables) of the above-mean unemployment rate of a residential quarter:

(i) A composition effect: high unemployment rates can be related to the socio-economic status of the population. As residential segregation often leads to the concentration of populations with low incomes and/or low educational attainments, the probability of the people living in these neighbourhoods to be unemployed is necessarily above the mean, whatever their physical access to jobs opportunities.

(ii) A transportation effect: the absence of car ownership or of public transit in an area can reduce its employment outcomes.

(iii) A spatial hysteresis or "ghetto" effect: the concentration of poorest people can lead to spatial discrimination against job seekers and reduce their access to informal social networks often used to access to jobs opportunities. As a consequence, a spatial hysteresis effect may operate and overestimate the unemployment rate without considering distance to job opportunities.

(iv) A spatial mismatch effect: jobless neighbourhoods can affect employment opportunities through increasing transportation and job-search costs.

We have interest in distinguishing clearly the spatial mismatch effect from the three other explanations. Indeed, the effect of physical access to job opportunities could result in an overestimation of the spatial mismatch effect.

As a consequence, the resulting general model for estimating the district unemployment rate is:

$$u_j = \alpha + \beta(x_{1j}, ...x_{kj}) + \gamma(S_{j(d)} / D_{j(d)})$$

Where, u_j is the unemployment rate for the working age population of the residential quarter section area j; x_{1j}, ... x_{kj} is a matrix of characteristics of j quarter section's residents that consider the composition effect, the residential segregation effect and the transportation effect *i.e.* k independent variables. Hence, the *x[kj]* matrix groups together, for each j residential quarter section area, the main characteristics of socio-economic status such as the age, gender, educational attainment and race, the pure residential segregation measured with data of the structure of the housing market, see as an example the proportion of low-rent habitations, and the transportation effect such as the proportion of car ownership. As a consequence, β is expected to be positive and the unemployment rate may vary widely according to smaller residential areas as residential quarter section area. Hence, this smaller geographical unit is the most appropriate to measure and control the effect of socio-economic composition, pure residential segregation or transportation capabilities.

Following Simpson (1992) and Immergluck (1998), the model presented in equation 1 requires another geographical unit to make the ratio of jobs opportunities exogenous to resident's unemployment. Indeed, the quarter section's residents seeking for nearby jobs are more likely to find work in some larger and surroundings areas than in the quarter section j itself. As a consequence, we introduce a circular job catchment area of radius d, surrounding and including the smaller area *i.e.* the quarter section j within the city. These circular catchment areas of radius d measure the direct opportunity and competition to jobs in that area. The spatial mismatch effect is then measured according to the ratio $S_{j(d)} / D_{j(d)}$: the density of jobs supply $S_{j(d)}$ compared to jobs demand $D_{j(d)}$ within distance d to the centre of each quarter section j. Hence, γ is expected to be negative: the local unemployment rate should decrease as the density of jobs opportunities increase.

The central question is whether distance is a fundamental variable in spatial mismatch hypothesis. In most previous studies, distance is arbitrarily defined and the authors surprisingly do not discuss its impact on spatial friction. As an example, authors use residential areas (Gobillon and Selod, 2002) or job catchment areas larger than the quarter section but with an *a priori* distance (refer to the radius of 2 miles around each residential zone or quarter section in Immergluck, 1998).

The originality of our study is to consider distance as a continuous variable that enables to build circular areas from the centre of each residential quarter and of increasing radius to measure the impact of larger areas of job opportunities on unemployment rates at the local level of the quarter section. The main limits of this approach are the following:

(i) Firstly, the distance we consider is a Euclidian distance that rules out the structural form of commuting times or distances within the city (direction and cost transportation as an example).

(ii) Secondly, there exist necessarily some edge effects that limit the maximum value of the radius to consider. Indeed, beyond 15 kilometres around a city quarter, the whole employment regional market is considered. This maximum distance matches with the mean of commuting times in France *i.e.* 18 minutes in 1998 (see INSEE transport survey).

(iii) As a consequence, and finally, considering increasing distance (higher radius around the centre of a quarter, surrounding and including each quarter) tend to considering convergent and similar areas of job densities.

A major concern of this paper is also to stress the impact of spatial hysteresis depending on the friction of distance. The impact of spatial hysteresis on quarter sections' unemployment rates is estimated here in replacing the u_j dependant variable in equation (1) by u_{jld}, the long term unemployment rate recorded in each residential quarter section area *j i.e.* people that are unemployed for more than a year in a quarter section.

$$u_{jlt} = \alpha + \beta(x_{j1},.........x_{jk}) + \gamma(S_{j(d)} / D_{j(d)}) \qquad (2)$$

Literally, we tend to explain the increasing level of long term unemployment however the level of local unemployment rate it may be. Indeed, the above-mean unemployment rate of a residential quarter may be linked to a structural phenomenon associated with the nature of unemployment and the spatial configuration of districts. Also, as presented in equation (1) or (2), the model may problem a positive spatial autocorrelation: pair of nearby observations may be more similar than those of more distant pairs. As a consequence, we have to estimate an econometric model controlling for spatial autocorrelation.

II-1.2 The data

The data used for the estimation of local unemployment are derived from the 1999 French national institute of statistics and economics studies (INSEE) and the 1999 French National Agency for Employment (ANPE). The interest of the data base is to mix a set of spatial characteristics of residents, job seekers and employment offers at small geographical levels. The INSEE data provide information on residents and working population aggregated at the residential quarter section level. The ANPE data enable to catch directly data about job seekers and employment offers whereas most of precedent studies used the total number of jobs as a proxy for job opportunities.

Despite their intrinsic interest, ANPE data suggest some debatable points. The approach is grounded on job supply (recorded opportunities, advertised jobs) and on job demand (job seekers at the end of the month) listed by cities within the Bordeaux metropolitan area. We assume that located supply and located demand correspond to territorial realities, able to give evidence of local labour markets. Moreover, to cross these data with INSEE data source, recorded supply (flow) and demand for jobs (stock) have been replaced by annual averages at the city level. Thus the interest of this data set may be counterbalanced by the aggregated geographical unit of these data *i.e.* the city level.

As we need to cross INSEE and ANPE data bases at the same and smaller geographical unit for estimating equations (1) and (2), we need to distribute the ANPE data along the INSEE residential quarter section areas (IRIS 2000). We choose the following distribution system:

(i) Employment offers are allocated from the city level to the residential quarter geographical level according to the area of each residential quarter section.

(ii) ANPE job seekers are divided out according to the amount of 1999 unemployment in each IRIS section.

With our data restriction to the smaller geographic unit (to grasp an effect of the quarter section on local above-mean unemployment), we consider this distribution key of population among quarter sections, to be the best one available. It takes into account both the quarter section INSEE unemployment size and the density of job supply as a variable of competition to jobs in each quarter section.

The geographical framework of the analysis is the Bordeaux metropolitan area. After excluding observations in which there was insufficient population to calculate variables of concern and those which were spatially remote (*i.e.* 4 residential quarter sections), the resulting data set consist of 420 residential quarter sections. Hence, cities of the Bordeaux metropolitan area that are informed with ANPE data constitute a set of 420 quarter sections (INSEE IRIS).

Figure 1 (see appendix 1) illustrates unemployment rates across the study area. We observe that many of the quarter sections in the Bordeaux metropolitan area with high unemployment rates, above the mean of 14.5 per cent total, are clustered on quarter sections within the Bordeaux metropolitan central city.

To analyse the wide variability of such unemployment rates, we need to consider the characteristics of the population of the residential quarter sections. Indeed, the spatial structural form of the working population may have an impact on the above-mean unemployment rates. As an example, with 47% of the working population being women and 31% having a high school diploma, the residential segregation may be influenced by the composition effect. Moreover, distance may have an impact on the unemployment rates. As the job catchment areas increase, table 1 shows that the mean of the quarter sections' ratio of job opportunities to job seekers tends to decrease. Table 1 provides the descriptive statistics for the dependent variable and the independent variables used to estimate equation (1) and (2).

Figures 2 to 6 show the spatial pattern of the ratio of job opportunities to job seekers ($S_{j(d)} / D_{j(d)}$) for five radius of 1, 3, 8, 10 and 15 km. We observe that measuring the number of job opportunities by job seeker with different sizes of job catchment areas leads to non redundant results. With small areas (figures 2 and 3), a much diversified "patchwork" emerges with an important number of jobless areas adjacent to quarter sections with high job opportunities densities. When considering areas with a radius over 8 km (Figures 4 to 6), an important regional mismatch appears, opposing a large jobless area going from north-east to south-east to a more privileged region, from north-west to south west.

It seems that two different spatial frictions are involved in this dual pattern. As stressed in the precedent section, the spatial mismatch hypothesis relates to two types of spatial frictions. The first one, related to prohibitive commuting times or distances, implies somewhat important distances, and could thus be measured by the large job catchment areas from 8km to 15km. The second one, as a result of the job seeking behaviour, can be related to more local areas, from 1 to 5 km. The empirical framework proposed in the next section will allow to test the hypothesis of a dual spatial friction involved in the spatial mismatch mechanism.

Figure 2. ratio $S_{j(d)} / D_{j(d)}$ with a radius of 1 km

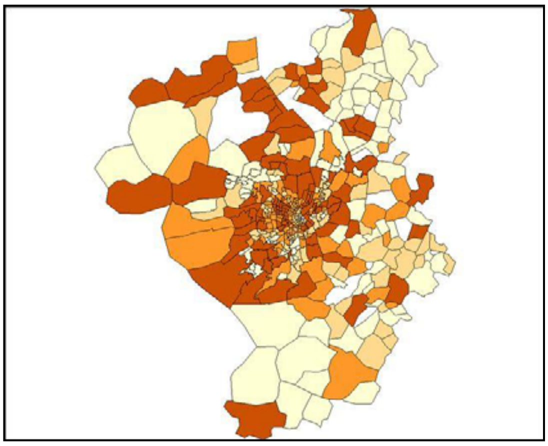


Figure 3. ratio $S_{j(d)} / D_{j(d)}$ with a radius of 3 km

Figure 4. ratio $S_{j(d)} / D_{j(d)}$ with a radius of 8 km

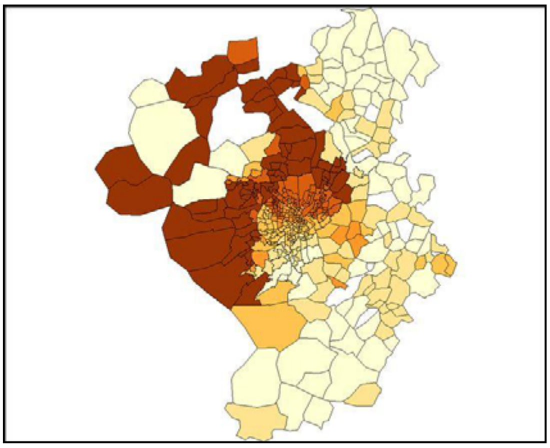


Figure 5. ratio $S_{j(d)} / D_{j(d)}$ with a radius of 10 km

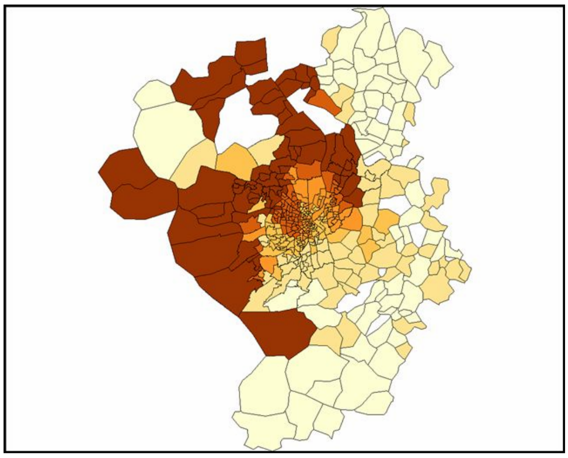


Figure 6. ratio $S_{j(d)} / D_{j(d)}$ with a radius of 15 km

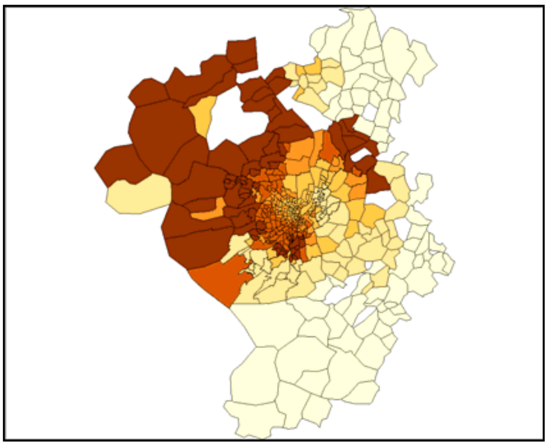


Table 1. Summary statistics for dependent and independent variables

Variable name	Abbreviation	Variable description	Mean	Standard deviation
Unemployment rate	u	Job seekers (ANPE 1999) / working population (INSEE 1999)	0.14	0,05
Long term unemployment rate	u_{lt}	Job seekers for more than a year being unemployed (INSEE 1999) / working population (INSEE 1999)	0.08	0.038
Young working population	PYOU	Proportion of residents in the working population who are under 25 (INSEE 1999)	0.08	0.03
Female working population	PFEM	Proportion of residents in the working population who are female (INSEE 1999)	0.47	0.03
high-school education attainment	PPRIM	Proportion of residents who are more than 15 and no more students, with high-school diploma or equivalent (under the school leaving certificate taken at 17-18) (INSEE 1999)	0.31	0.10
Low-rent habitations	PLRH	Proportion of low-rent apartments and low-rent houses (INSEE 1999)	0.11	0.20
Non car ownerships	P0CAR	Proportion of residents who don't have a car (INSEE 1999)	0.16	0.12
Foreigner working population	PFOR	Proportion of residents in the working population who are foreigners (INSEE 1999)	0.04	0.04
Job catchment area	S/D Km	Density of jobs supply (ANPE 1999) compared to jobs demand (INSEE 1999) within distance *d* Km to the centre of each district		
		Km = 1	1.32	7.02
		Km = 5	0.79	0.68
		Km = 8	0.81	0.46
		Km = 15	0.79	0.17

ANPE French National Agency for Employment

INSEE French national institute of statistics and economics studies

II-2 Results

II-2.1 The validation of the theoretical framework of the SMH

Table 2 presents the results of the ordinary least squares regression (OLS estimates) for estimating equations (1) and (2). The two first columns show results for equation (1), the two second ones illustrate results for equation (2).

The regression results indicate that the theoretical framework of the SMH is not denied. All independent variables of equation (1) are significant at 10%. As expected, the composition effect (PYOU, the proportion of young working population; PFEM, the proportion of the female working population and PPRIM, the proportion of high school educational attainment), the pure residential segregation effect (PLRH, the proportion of low-rent habitations), the transportation effect (P0CAR, the proportion of none car ownership) are positively related to neighbourhood unemployment and long term unemployment, respectively with an adjusted[4] R^2 fit of 0.806 and 0.757. As expected, the spatial friction of job catchment area (S/D 2km) is negatively related to the neighbourhood unemployment rate and to the long term unemployment rate. We have to discuss the sign of the influence of the proportion of the female working population on the global unemployment rates and the long term unemployment rates as it was expected to be positive. Indeed, this negative effect could be explained by the fact that the female proportion of working population is inferior to the male one, so that women are less supposed to be declared unemployed. Immergluck (1998) sets a similar result.

Table 2. OLS estimations and tests of spatial dependence

Equation	**(1) Global unemployment rate**		**(2) Long term unemployment rate**	
	coeff	**t-value**	**coeff**	**t-value**
CONSTANT	0,0852	*2,8959*	0,0397	*1,8907*
PYOU	0,1765	*3,1411*	0,0748	*1,8658*
PFEM	-0,1115	*-2,0093*	-0,0617	*-1,5587*
PPRIM	0,1239	*8,1093*	0,1024	*9,3896*
PLRH	0,0444	*4,9568*	0,0420	*6,5723*
P0CAR	0,2342	*15,7748*	0,1208	*11,4025*
PFOR	0,3938	*9,5238*	0,2282	*7,7337*
S/D 2km	-0,0005	*-2,0445*	-0,0007	*-3,8785*
R2-adj	0,806		0,757	
LIK	932,151		1072,490	
AIC	-1848,300		-2128,980	
SC	-1816,060		-2096,730	
Koenker-B. test	84,260	0,000	71,664	*0,000*
White test	188,048	0,000	217,523	*0,000*
Moran 's I (error)	5,659	0,000	5,041	*0,000*
LM (error)	27,958	0,000	21,910	*0,000*
Robust LM (error)	12,454	0,000	4,332	*0,037*
LM (lag)	17,155	0,000	23,943	*0,000*
Robust LM (lag)	1,651	0,199	6,366	*0,012*

4 The pseudo R² is equal to the ratio of the variance of the predicted values of the dependent variable to the observed values of the dependent variable.

A potential bias may come from a sort of women self-censorship supposing that women might not anticipate the opportunities of neighbourhood jobs.

Table 2 suggests that there are quite a few specification problems.

Some variables of the composition effect (PYOU, the proportion of young working population; PFEM, the proportion of the female working population) are not significant in equation (2). We must give attention to the possibility that the variables or the errors in the model show spatial dependence. Indeed, the high R^2 value combined with low *t* statistics may problem multicollinearity and the Koenker-Basset and White tests suggest that heteroskedasticity is clearly an issue in equations (1) and (2).

The spatial weight matrix used to run the tests of spatial dependence is a first-order contiguity matrix. The structure of connectivity is concentrated around a mean of 5.37 and a median of 5.6 neighbours by quarter section. As shown in figure 7, the histogram is symmetric, and there are no "islands" without neighbours.

Figure 7. Histogram of the connectivity structure of the spatial weigh matrix

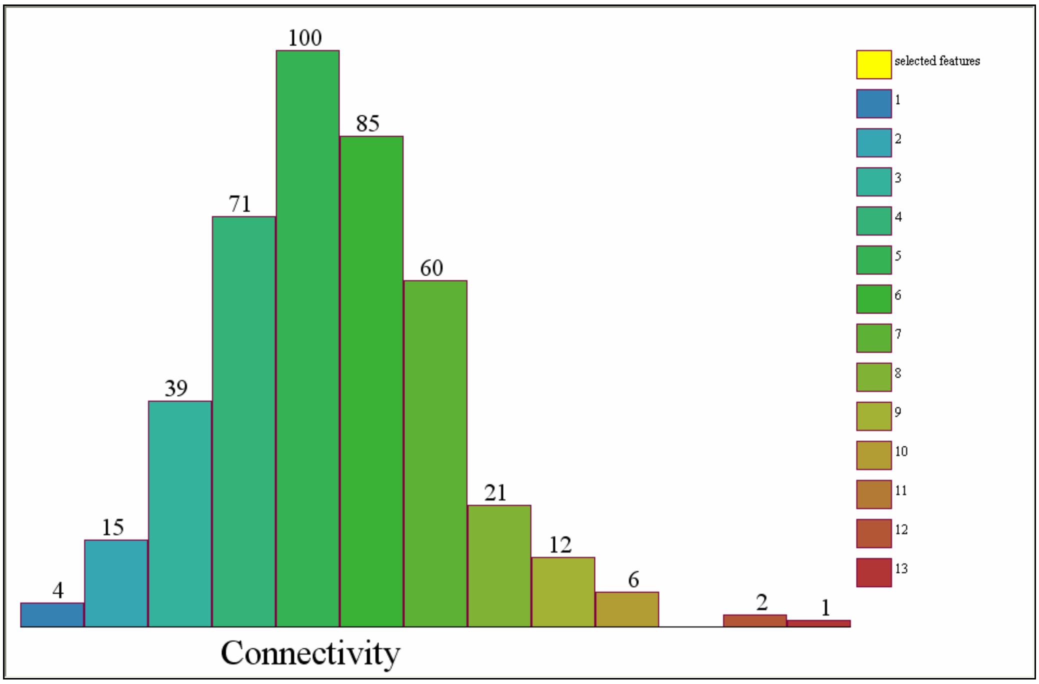


Table 2 shows that spatial autocorrelation is clearly a problem. Moran's I, LM-Error, LM-Lag and the White test are all significant. We have to note that in equation (1) the LM-error test (27.9) is larger in magnitude than the LM-lag test (1.6) which would suggest that a spatial error specification is a proper alternative to equation (1). This is confirmed by the robust form of these tests, where the robust LM-lag is no longer significant and the LM-error still is. Note too that the proper alternative to equation (2) is at the opposite, a lag, which seems to be confirmed by the robust form of these tests.

The alternative specification of equation (2) matches with the theoretical framework of the spatial hysteresis hypothesis (SHH). More specifically, the fact that the spatial autoregressive model appears to be the best alternative to OLS only for the long term unemployment rate is consistent with the SHH. Most of the mechanisms invoked by the hysteresis hypothesis, such as the peer effects in educational attainments, are time-cumulative and affect the future employability of job seekers, and consequently must affect primarily the long term employment rate. As the spatial lag is a spatially weighted average of the neighbouring values of the dependent variable, using first order contiguity, the spatial autoregressive parameter can be considered as a measure of the neighbourhood negative externalities involved in the hysteresis mechanism. As a consequence, even if the spatial hysteresis process can be grounded on the residential segregation and/or on the spatial mismatch effect, they can be clearly distinguished from the SHH in the estimation of equation (2).

II-2.2 The impact of distance in the estimation of the SMH

We propose a range of tests with varying distance to discuss the effect of distance on the intensity of the spatial mismatch. Considering distance as a continuous variable, the alternative specifications of equations (1) and (2) have been estimated along with incrementing distance of 0.5km. Tables 3 and 4 present the results of maximum likelihood estimations for the alternative specifications of (1) and (2) and a set of varying distance, we illustrate with the examples characteristic of *d*=1, 5, 8 and 15 km.

First of all, the estimates for the autoregressive parameter of the error process are shown next to Lambda (table 3) for equation (1) and the estimates for the spatial autoregressive parameter are shown next to WU_{LT} (table 4) for equation (2). They are positive and significant, confirming the diagnostics in the OLS estimation (refer to table 2). In terms of fit, the maximized likelihood of the spatial lag model and spatial error model are larger than that of the classic regression, confirming the appropriateness of the alternative specification of equations (1) and (2) in distance.

Secondly, the regression results indicate that all independent variables are not continuously significant in distance. It is particularly the case for the impact of the proportion of female working population (PFEM) on neighbourhood unemployment rates.

Table 3. Spatial error model of global unemployment rate in distance

Equation (1): Global unemployment rate, Maximum Likelihood Estimations

	1km		**5km**		**8km**		**15km**	
	coeff	z-val	coeff	z-val	coeff	z-val	coeff	z-val
CONSTANT	0,0803	*2,6837*	0,0396	*1,3656*	0,0459	*1,5921*	0,0617	*2,1197*
PYOU	0,2342	*4,2293*	0,1891	*3,4172*	0,1922	*3,4939*	0,1988	*3,6346*
PFEM	-0,0954	*-1,6782*	-0,0078	*-0,1445*	-0,0089	*-0,1653*	0,0069	*0,1292*
PPRIM	0,1092	*6,3134*	0,1154	*6,4831*	0,1137	*6,4706*	0,1014	*5,6926*
PLRH	0,0486	*5,5607*	0,0439	*4,9656*	0,0433	*4,9238*	0,0447	*5,1199*
P0CAR	0,2189	*12,8382*	0,2178	*12,3291*	0,2143	*12,2470*	0,2188	*12,7925*
PFOR	0,3833	*9,3521*	0,4191	*10,2318*	0,4310	*10,5006*	0,4359	*10,6917*
S/D	**-0,0008**	***-4,1012***	**-0,0008**	***-0,4558***	**-0,0074**	***-2,3670***	**-0,0342**	***-3,3961***
Lambda	**0,3530**	***5,4367***	**0,3759**	***5,8915***	**0,3649**	***5,6702***	**0,3480**	***5,3393***
R2	0,8316		0,8256		0,8275		0,8294	
LIK	952,310		944,254		946,9064		949,7200	
AIC	-1888,6		-1872,51		-1877,81		-1883,44	
SC	-1856,3		-1840,26		-1845,56		-1851,19	
B-P	98,288	*0,000*	147,258	*0,000*	151,4468	*0,000*	141,4866	*0,000*
Spat B-P	98,288	*0,000*	147,258	*0,000*	151,4468	*0,000*	141,4866	*0,000*
LR	24,4305	*0,000*	26,4067	*0,0000*	25,2882	*0,0000*	22,8217	*0,0000*

Table 4. Spatial lag model of long term unemployment rate in distance

Equation (2): Long term unemployment rate, Maximum Likelihood Estimations

	1km		5km		8km		15km	
	coeff	z-val	coeff	z-val	coeff	z-val	coeff	z-val
WU_{LT}	**0,2292**	***5,2583***	**0,2186**	***4,8910***	**0,2169**	***4,8637***	**0,2033**	***4,5887***
CONSTANT	0,0533	*2,5739*	0,0207	*1,0172*	0,0244	*1,2047*	0,0319	*1,5801*
PYOU	0,1135	*2,9375*	0,0773	*1,9723*	0,0799	*2,0491*	0,0888	*2,2955*
PFEM	-0,103	*-2,624*	-0,034	*-0,906*	-0,035	*-0,929*	-0,017	*-0,461*
PPRIM	0,0720	*6,4862*	0,0834	*7,4922*	0,0805	*7,2102*	0,0447	*7,2486*
PLRH	0,0503	*8,1203*	0,0440	*7,0261*	0,0437	*7,0213*	0,0722	*6,3580*
P0CAR	0,0888	*8,0166*	0,0916	*8,0587*	0,0893	*7,8680*	0,0916	*8,1565*
PFOR	0,1913	*6,7065*	0,2165	*7,3666*	0,2250	*7,6131*	0,2331	*7,9704*
S/D	**-0,0007**	***-5,327***	**-0,002**	***-1,344***	**-0,005**	***-2,482***	**-0,022**	***-3,932***
R2	0,778		0,764		0,766		0,772	
Sq,	0,783		0,768		0,771		0,776	
LIK	1090,0		1077,1		1079,3		1083,9	
AIC	-2161,9		-2136		-2140		-2149	
SC	-2125,7		-2100		-2104		-2113	
B-P	145,10	*0,000*	192,31	*0,000*	193,75	*0,000*	174,71	*0,000*
Spat B-P	145,10	*0,000*	192,31	*0,000*	193,75	*0,000*	174,71	*0,000*
LR	25,895	*0,000*	22,479	*0,000*	22,300	*0,000*	19,795	*0,000*
LM	0,899	*0,343*	1,954	*0,162*	2,228	*0,136*	1,769	*0,184*

Nevertheless, the proportion of female working population less than 5 km from their residential quarter has a significant negative impact on neighbourhood long term unemployment, which confirms the hypothesis of a self-censorship effect. Moreover, the proportion of young working population (PYOU) is only non-significant at 5 km on neighbourhood long term unemployment rates. Both in the spatial lag model and the spatial error model, there is still evidence of remaining heteroskedasticity (see Breush-Pagan and likelihood ratio test for spatial error dependence (table 3) and Breush-Pagan and Lagrange Multiplier test for heteroskedasticity (table 4)).

Appendix 2 provides viable alternatives to maximum likelihood estimations for both the spatial error model of neighbourhood global unemployment rates and the spatial lag model of neighbourhood long term unemployment rates. Results in appendix 2 make it reasonable to keep comments validating the theoretical framework of the SMH. Moreover, the estimates are very similar in magnitude between the maximum likelihood estimation and alternatives such as the weighted maximum likelihood or the bootstrap estimation.

Finally, table 3 and 4 show interesting results concerning the impact of distance in the estimation of the SMH. As expected, whatever the radius *d* of the circular job catchment area surrounding and including each residential quarter section, the spatial friction (S/D km) is negatively related to the global unemployment rate and to the long term unemployment rate. Indeed, an enlarged area of job opportunities might have a negative impact on neighbourhood unemployment or on neighbourhood long term unemployment rates. Nevertheless, it is interesting to note that the parameter of spatial friction is not continuously significant in distance. In particular, the spatial friction parameter is significant:

(i) when considering short distances, below 2 km. It suggests a local effect of jobs catchment areas on the neighbouring long term or global unemployment rates. This result validates the hypothesis of the influence of a neighbouring effect on the estimation of the SMH.

(ii) when regarding larger distances, from 8 km to 15 km, suggesting a regional effect of jobs catchment areas on the neighbouring long term or global unemployment rates. Beyond 15km around each residential quarter, job opportunities areas meet the regional labour market opportunities. As a consequence, the spatial friction estimates stabilize to become non-significant.

These results must be related to the spatial pattern of the ratio of job opportunities to job seekers shown above, in figures 2 to 6. The distances below 2 km correspond to the patchwork pattern of dispersed small jobless areas, whereas the distances from 8 to 15 km match precisely with the regional east/west disiquilibrium. These results are thus consistent with the hypothesis of a dual feature of the friction of distance, combining a short distance effect related to job seeking behaviour through informal vectors with a regional effect resulting from the commuting costs implied by the east/west disiquilibrium pattern. This dual effect is furthermore consistent with the theoretical foundations of the spatial mismatch hypothesis combining different spatial frictions.

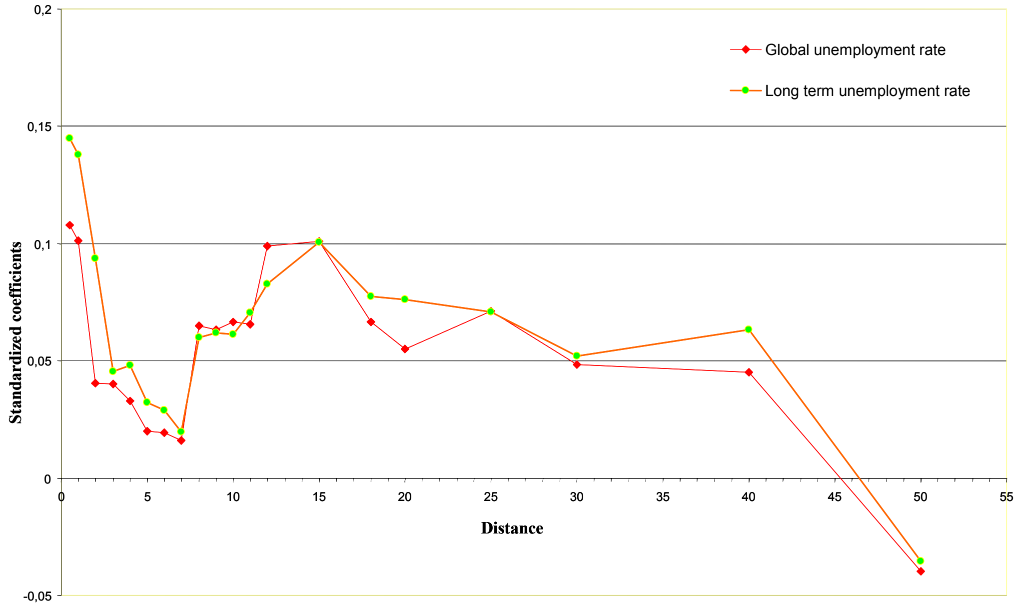
In terms of fit, the model with the highest log-likelihood (LIK) or with the lowest Akaike Information Criterion (AIC) or Schwartz criterion (SC) is best. Thus, the SMH is dependent on a local and a regional phenomenon, regardless of the capabilities of job seekers to commute. These results confirm the existence of a varying effect of spatial friction depending in distance. If spatial friction is found to have a varying negative effect in distance on unemployment rates and long term unemployment rates, the size of the effect, as revealed in the standardized coefficients or the β-values is quite modest.

Figure 8 illustrates this influence. Standardized coefficients are calculated by multiplying parameter coefficients by the ratio of the standard deviation of the independent variable to the standard deviation of the dependent variable. It sets two main results:

(i) An increase of a standard deviation of the spatial friction of jobs catchment area results in a decrease of neighbourhood unemployment rates of 0.12 standard deviation (0.6%) at 1 km from each residential quarter section whereas it falls to a part of 0.04 standard deviations (0.2%) considering a job catchment area of 3 km. The impact of job opportunities areas on local unemployment rates rises from 0.07 standard deviation (a decrease of 0.35% of the neighbouring unemployment rates) when considering a job catchment area of 8 km, to 0.1 standard deviation (a decrease of 0.5% of the neighbouring unemployment rate) within a 15 km area of job opportunities.

(ii) The influence of the size of job catchment areas is different when considering long term or global unemployment rates. Indeed, the intensity of the neighbouring spatial friction effect on the long term unemployment rates is higher than the effect on the unemployment rates: the decrease of long term unemployment is of 0.15 standard deviation when considering job catchment areas of 1 km whereas the decrease of global unemployment is only of 0.12 standard deviation. It is only of 0.03 unemployment standard deviation compared to 0.09 long term unemployment standard deviation from 3 km job opportunities areas. Hence, the spatial hysteresis effect is clearly shown in figure 1. It appears as a pure residential quarter phenomenon that focuses on particular structural populations such as long term unemployed people.

Figure 8. Intensity of the spatial mismatch in distance



II-2.3 The marginal effect of distance in the estimation of Spatial Mismatch Hypothesis

As shown in figure 7, the coefficient of the spatial friction remains significant beyond 15 Km, until 40 km. On can think this pattern to be the consequence of a bias resulting from the construction of the job catchment areas (cf. table 1) : as the standard deviation of unemployment rates are decreasing with increasing size of the areas, the coefficient related to an area of radius i can include, for a great part, the effect resulting from the competition for jobs within smallest areas. It is thus necessary to appreciate the marginal impact of distance in the estimation of the SMH.

For that, we need to estimate the influence of an increase of job catchment areas on the residential quarter long term and global unemployment rates. We thus define for each spatial ring a measure of the spatial friction (*S/D*) when increasing the radius of the job catchment areas from the centre of each residential quarter section. Considering *k* as the incremental distance of the job catchment area, a spatial ring *r* is processing as follows:

$$(S\ /D\ )_{ring\quad r} = \frac{S_{j(d+k)} - S_{j(d)}}{D_{j(d+k)} - D_{j(d)}}$$

Tables 5 and 6 present the results for the four main spatial rings considering job catchment areas: from 2 to 5 km, 5 to 8 km, 8 to 15 km and 15 to 20 km from the centre of each residential quarter section.

If previous comments on the theoretical framework of the SMH remain, the spatial ring analysis shows that the spatial mismatch effect is negative and significant both within 5 to 8 km and 8 to 15 km from the centre of each residential quarter section. Spatial mismatch is clearly distinguished from a neighbouring effect that the spatial hysteresis effect is able to grasp. Here, the highest log-likelihood or the lowest Akaike Information Criterion (AIC) and Schwartz criterion (SC) show in tables 5 and 6 that the spatial mismatch effect runs particularly in areas of 8 to 15 km from the centre of each residential quarter section. Nevertheless, the ring from 15 to 20 km appears no longer significant, indicating that beyond 15 km, the significant value of the coefficient describing spatial friction (as shown in figure 8) is purely the result of a construction bias.

Table 5. Spatial error model of global unemployment rate considering distance rings

	2 to 5 km		5 to 8 km		8 to 15 km		15 to 20 km	
	coeff	z-val	coeff	z-val	coeff	z-val	coeff	z-val
CONSTANT	0,0388	*1,3384*	0,0416	*1,4480*	0,0488	*1,6943*	0,0321	*1,0913*
PYOU	0,1887	*3,4088*	0,1914	*3,4748*	0,1936	*3,5157*	0,1879	*3,3990*
PFEM	-0,0064	*-0,1186*	-0,0050	*-0,0937*	0,0023	*0,0419*	-0,0028	*-0,0516*
PPRIM	0,1150	*6,4567*	0,1129	*6,3891*	0,1055	*5,8983*	0,1139	*6,3921*
PLRH	0,0440	*4,9713*	0,0432	*4,9063*	0,0435	*4,9545*	0,0436	*4,9279*
P0CAR	0,2179	*12,3101*	0,2156	*12,2974*	0,2276	*13,1045*	0,2211	*12,3333*
PFOR	0,4189	*10,2267*	0,4277	*10,4347*	0,4181	*10,2742*	0,4172	*10,1993*
S/D	**-0,0005**	***-0,2727***	**-0,0038**	***-2,0955***	**-0,0158**	***-2,3484***	**0,0059**	***1,0247***
Lambda	0,3788	*5,9494*	0,3688	*5,7483*	0,3322	*5,0390*	0,3774	*5,9214*
R2	0,788		0,791		0,795		0,790	
Sq C	0,805		0,808		0,812		0,806	
LIK	944,190		946,320		946,630		944,676	
AIC	-1872,30		-1876,60		-1877,26		-1873,35	
SC	-1840,13		-1844,39		-1845,01		-1841,11	
B-P	148,403	*0,000*	153,108	*0,000*	148,155	*0,000*	142,466	*0,000*
Spatial B-P	148,406	*0,000*	153,112	*0,000*	148,158	*0,000*	142,470	*0,000*
LR	27,232	*0,000*	25,674	*0,000*	19,182	*0,000*	26,939	*0,000*

Table 6. Spatial lag model of long term unemployment rate considering distance rings

	2 to 5 km		5 to 8 km		8 to 15 km		15 to 20 km	
	coeff	z-val	coeff	z-val	coeff	z-val	coeff	z-val
WU_{LT}	0,2202	*4,9242*	0,2154	*4,8292*	0,1930	*4,3117*	0,2149	*4,7960*
CONSTANT	0,0200	*0,9841*	0,0220	*1,0893*	0,0207	*1,0336*	0,0140	*0,6805*
PYOU	0,0762	*1,9452*	0,0786	*2,0129*	0,0860	*2,2081*	0,0758	*1,9325*
PFEM	-0,0338	*-0,8810*	-0,0329	*-0,8632*	-0,0109	*-0,2820*	-0,0286	*-0,7444*
PPRIM	0,0831	*7,4584*	0,0805	*7,1962*	0,0763	*6,7545*	0,0837	*7,5285*
PLRH	0,0440	*7,0259*	0,0433	*6,9410*	0,0431	*6,9429*	0,0433	*6,8846*
P0CAR	0,0920	*8,1016*	0,0907	*8,0185*	0,1007	*8,7586*	0,0950	*8,1965*
PFOR	0,2153	*7,3279*	0,2223	*7,5453*	0,2173	*7,4872*	0,2115	*7,2127*
S/D	**-0,0014**	***-1,1077***	**-0,0030**	***-2,3023***	**-0,0124**	***-3,1768***	**0,0031**	***0,8862***
R2	0,764		0,766		0,769		0,763	
Sq C	0,768		0,770		0,772		0,768	
LIK	1076,880		1078,900		1081,190		1076,660	
AIC	-2135,7		-2139,8		-2144,3		-2135,3	
SC	-2099,4		-2103,5		-2108,1		-2099,0	
B-P	194,374	*0,000*	194,255	*0,000*	186,157	*0,000*	195,605	*0,000*
Spatial B-P	194,375	*0,000*	194,256	*0,000*	186,158	*0,000*	195,606	*0,000*
LR	22,777	*0,000*	21,935	*0,000*	17,214	*0,000*	21,373	*0,000*
LM	2,240	*0,134*	2,550	*0,110*	1,254	*0,263*	2,874	*0,090*

Concluding remarks

This article analyses the links between residential segregation and local labour markets. A theoretical framework is built in a first part allowing to distinguish the spatial mismatch effect from the residential effect, the accessibility to job opportunities and the spatial hysteresis effect. Spatial mismatch is considered as a spatial friction defined by the distance between residential quarters and job opportunities. The interest of this approach is double:

(i) First of all, spatial friction is grasped through the development of an original indicator of jobs opportunities related to jobs demand. The calculus of such an indicator is possible thanks to specific ANPE data

(ii) Secondly, a range of tests with varying distance allows to investigate the scale and the nature of the spatial friction involved in the spatial mismatch..

Three main results can be raised:

(i) the results obtained confirm the relevance of the spatial mismatch hypothesis, although the quantitative influence on local unemployment rates appears to be quite modest. The same conclusion is obtained by Immergluck (1998).

(ii) Using an original framework to analyse the spatial mismatch with a varying distance of friction, we have identified two scales of spatial friction, one operating within small areas (below 2 km) and corresponding to informal job-search behaviour and the other relating to commuting distances resulting from a regional unbalanced structure between the east and west parts of the urban area.

(iii) Comparing the diagnostics of spatial autocorrelation for the global and long-term unemployment rates we have stressed a spatial hysteresis mechanism affecting specifically the long term unemployment.

The distinction between the spatial hysteresis effect and spatial mismatch hypothesis appears of a great interest. As stressed before, the reduction of the employment probabilities of job seekers in presence of spatial hysteresis is not directly tied to the presence of suitable nearby jobs. One could thus understand the persistence of neighbourhood-specific high unemployment rates in areas in other respects exhibiting a good accessibility to job opportunities. Furthermore, policies aiming at reducing unemployment in these areas must address directly the segregation mechanisms leading to the concentration of jobless and/or low income households, instead of promoting the relocation of jobs near to these neighbourhoods. Finally, more work will be needed to identify the nature and the temporal dynamic of these spatial hysteresis mechanisms.

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Appendix 1

Figure 1: 1999 unemployment rates in Bordeaux metropolitan area

Appendix 2. Alternatives to maximum likelihood estimations

Spatial error model of global unemployment rate in distance

Equation (1): Global unemployment rate, Weighted Maximum Likelihood Estimations

	1km				15km			
	ML		Weighted ML		ML		Weighted ML	
	coeff	z-val	coeff	z-val	coeff	z-val	coeff	z-val
CONST	0,0803	*2,6837*	0,1211	*4,0547*	0,0617	*2,1197*	0,0187	*0,6954*
PYOU	0,2342	*4,2293*	0,1322	*2,5870*	0,1988	*3,6346*	0,2050	*3,8223*
PFEM	-0,0954	*-1,6782*	-0,1631	*-2,7844*	0,0069	*0,1292*	0,1362	*2,7930*
PPRIM	0,1092	*6,3134*	0,1167	*6,4972*	0,1014	*5,6926*	0,0765	*4,1623*
PLRH	0,0486	*5,5607*	0,0459	*3,6226*	0,0447	*5,1199*	0,0417	*3,1330*
P0CAR	0,2189	*12,8382*	0,2090	*9,6987*	0,2188	*12,7925*	0,1722	*7,6556*
PFOR	0,3833	*9,3521*	0,3341	*7,6949*	0,4359	*10,6917*	0,4625	*11,0773*
S/D	**-0,0008**	***-4,101***	**-0,0008**	***-7,5688***	**-0,0342**	***-3,3961***	**-0,0421**	***-3,9276***
Lambda	**0,3530**	***5,4367***	**0,3426**	***5,2351***	**0,3480**	***5,3393***	**0,3784**	***5,9409***
R2	0,8316		0,649		0,8294		0,668	
LIK	952,3102		789,007		949,720		770,145	
AIC	-1888,62		-1562,01		-1883,44		-1524,2	
SC	-1856,37		-1529,7		-1851,19		-1492,0	
B-P	98,288	*0,000*			141,486	*0,000*		
Spat B-P	98,288	*0,000*			141,486	*0,000*		
LR	24,4305	*0,000*			22,8217	*0,0000*		

Spatial lag model of long term unemployment rate in distance

Equation (2): Long term unemployment rate, Maximum Likelihood Estimations

	ML		IV robust		IV Bootstrap	
	coeff	*z-val*	coeff	*z-val*	coeff	*z-val*
WU_{LT}	**0,2292**	***5,2583***	**0,2155**	***3,1485***	**0,2004**	***3,0990***
CONSTANT	0,0533	*2,5739*	0,0771	*3,1431*	0,0560	*2,4118*
PYOU	0,1135	*2,9375*	0,1103	*2,6559*	0,1171	*2,8855*
PFEM	-0,1038	*-2,6244*	-0,1468	*-3,2159*	-0,1078	*-2,4737*
PPRIM	0,0720	*6,4862*	0,0620	*4,7303*	0,0735	*6,2011*
PLRH	0,0503	*8,1203*	0,0560	*6,8219*	0,0503	*7,9321*
P0CAR	0,0888	*8,0166*	0,0986	*7,7336*	0,0920	*7,5842*
PFOR	0,1913	*6,7065*	0,1622	*3,5408*	0,1942	*6,9149*
S/D1km	**-0,0007**	***-5,3274***	**-0,0010**	***-4,7291***	**-0,0007**	***-5,1132***
R2	0,778		0,776		0,786	
Sq	0,783		0,779		0,773	
LIK	1090,000					
AIC	-2161,990					
SC	-2125,720					
Breusch-P	145,103					
Sp B-P	145,103					
LR	25,895					
LM	0,899					