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ABSTRACT

Mismatch, Transport Mode and Search Decisions in England*

We develop a theoretical model in which whites mainly use private vehicles to commute whereas non-whites use public transportation. We show that, for whites and non-whites, higher (time) distance-to-jobs leads to lower search effort. Because of different transport modes, we also show that, at exactly the same (time) distance-to-jobs, white unemployed workers search more intensively than non-whites because it is less costly for them to gather information about jobs. We then test this model using English sub-regional data. We find that, for each race, living in areas where distance-to-jobs is higher means the unemployed search less than in areas with better job access. We also find that having access to a car increases search intensity for both whites and non-whites. Finally, closing the racial gap in car access and distance-to-jobs would considerably narrow the difference in search intensities between whites and non-whites.

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Keywords: ethnic minorities, job access, job search and spatial econometrics

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1 Introduction

In both the United States and Europe, the concentration of spatial problems in the poor areas of many cities/regions has intensified over the years. Most of these poor areas concentrate a large fraction of ethnic minorities. We do not have yet a clear understanding of the link between segregation and labor market outcomes of ethnic minorities. It may be because two seemingly unrelated issues are at stake: the location of workers and its consequences in the labor market.

A popular explanation that has been put forward is the spatial mismatch hypothesis, first formulated by Kain (1968). It states that, residing in urban segregated areas distant from and poorly connected to major centers of employment growth, black workers face strong geographic barriers to finding and keeping well-paid jobs. In the U.S. context, where jobs have been decentralized and blacks have stayed in the central part of cities, the main conclusion of the spatial mismatch hypothesis is to put forward the distance to jobs as the main culprit for the high unemployment rates among blacks.

Since the study of Kain, dozens of empirical studies have been carried out trying to test this hypothesis (see the surveys by Holzer, 1991, Kain, 1992, and Ihlanfeldt and Sjoquist, 1998). The usual approach is to relate a measure of labor-market outcomes, based on either individual or aggregate data, to another measure of job access, typically some index that captures the distance from residences to centers of employment. The weight of the evidence suggests that bad job access indeed worsens labor-market outcomes, especially for ethnic minorities, confirming the spatial mismatch hypothesis.

Another explanation put forward is transport mode. Indeed, differences in transport modes between blacks and whites as an explanation of black-white unemployment rate differentials is something that is well-documented in the US. The general idea is that black workers who mainly use public transportation may refuse jobs involving too long commutes.[1] They may prefer to search for job opportunities at the vicinity of their neighborhood. Zax and Kain (1996) have illustrated this issue by studying a 'natural experiment' (the case

[1]In U.S. Metroplitan Statistical Areas, the lack of good public transportation is a real problem (see e.g. Pugh, 1998). For instance, the New York Times of May 26, 1998, was telling the story of Dorothy Johnson, a Detroit inner-city black female resident who had to commute to an evening job as a cleaning lady in a suburban office. By using public transportation, it took her two hours whereas, if she could afford a car, the commute would have taken only 25 minutes.

of a large firm in the service industry which relocated from the center of Detroit to the suburb Dearborn in 1974). Among workers whose commuting time was increased, black workers were over-represented, and not all could follow the firm. This had two consequences: first, segregation forced some blacks to quit their jobs. Second, the share of black workers applying for jobs to the firm drastically decreased (53% to 25% in 5 years before and after the relocation), and the share of black workers in hires also fell from 39% to 27%.

Both explanations are appealing and should be considered together. The aim of this paper is precisely to provide a simple theoretical model[2] that include both of these aspects and to test it using English data. To the best of our knowledge, there are very few empirical studies on these topics carried out in Europe.[3]

To be more precise, we first develop a theoretical model in which whites mainly use cars to commute to jobs whereas nonwhites use public transportation. We show that, for both whites and nonwhites, worse job access (long time distance to jobs) leads to lower search effort. Indeed, if unemployed workers have a bad access to jobs, then they will search less than those who have a better access because it takes more time (and it thus more costly) to gather information about jobs. Because of different transport modes, we also show that, at exactly the same time distance to jobs, white unemployed workers search more intensively than nonwhites. This is because whites use a private transport mode and thus can reach the center at a lower cost and, as a result, can gather more information about jobs than nonwhites.

We then test this model using NUTS3 level data in England. We use inter-area comparison to avoid questions of neighborhood selection commonly raised in intra-city tests. For a given area, we use as a proxy for time distance to jobs of the unemployed, the average commuting time of the employed living in the same area. Our empirical strategy is to investigate to what extent job seekers' search intensity is related to (time) distance to jobs and different transport modes (races), once the influence of other area specific characteristics have been controlled for.

We find that, indeed, living in areas where employed workers' average com-

[2]In fact, most of the papers cited above (testing the spatial mismatch hypothesis as well as transport modes) have no theoretical foundations. See Gobillon, Selod and Zenou (2003) for a survey of the theoretical models of the spatial mismatch.

[3]For the spatial mismatch, exceptions include Thomas (1998) and Fieldhouse (1999) for the UK and Dujardin, Selod and Thomas (2003) for Belgium. For the transport mode, exception includes Owen and Green (2000) for the UK.

muting time is higher yields the unemployed to search less than in areas with lower commuting time. We also find that having access to a car increases search intensity for both whites and nonwhites. The results provide strong evidence that differences in search activities between whites and nonwhites are due to both differences in job access as well as differences in car ownership.

We then use these estimated values of search intensities (purged by the effects of the other explanatory variables included in the econometric model estimated) for each race (white and nonwhite) and see how they change with different job accesses. We observe that, for a given time distance to jobs (here measured as the average commuting time of the employed), unemployed whites search more intensively than unemployed nonwhites. Finally, we explore to what extent inter-racial search effort differentials can be explained by whites-nonwhites car access and commuting time differences. More generally, closing the racial gap in car access and distance to jobs would considerably narrow the difference in search intensities between whites and nonwhites. In particular, having access to a car is a more important explanation of the racial difference in search intensities than distance to jobs.

2 Theoretical model

2.1 The model

There is a continuum of workers and firms. There are two types of workers: whites and nonwhites ($j = W, NW$). The mass of white and nonwhite workers are taken to be N_W and N_{NW}, respectively, while the total mass of workers is equal to 1, i.e. $N_W + N_{NW} = 1$. Whites and nonwhites are totally identical except for the fact that they do not use the same transport mode. We assume that whites mainly use private modes of transportation (cars) whereas nonwhites mainly use public transportation. This is a reasonable assumption since, for example in the US, nonwhites (especially blacks) essentially take public transport to commute to their workplace whereas whites use more their cars. To be more precise, using data drawn from the 1995 Nationwide Personal Transportation Survey, Raphael and Stoll (2001) show that, in the US, 5.4 percent of white households have zero automobile while 24 and 12 percent of respectively black and Latino households do not hold a single car.[4] Even more

[4]These differences indicate that black and Latino households are disproportionately represented among households with no automobiles. Indeed, while black and Latino households were respectively 11.5 and 7.8 percent of all households in 1995, they accounted for 35 and

striking, they show that respectively 64 and 46 percent of black and Latino households have one or zero car whereas this number was 36 percent for white households. In Great-Britain, using the 1991 Census data, Owen and Green (2000) show that people from minority ethnic groups are more than twice as likely as white people to depend on public transport for commuting journeys (33.2 versus 13.7 percent), with nearly three-fifths of Black-African workers use public transport to go to work. Furthermore, 73.6 percent of whites use private vehicle while this number is only 56.4 percent for ethnic minorities (and 39.6 percent for Black-African workers).

Let us analyze in more details the consequences of this assumption by focussing on individual decisions. For simplicity, we assume that the housing consumption is fixed and normalized to 1 for all workers (employed and unemployed). We focus on an area that has one big center of employment where all jobs are located.

The budget constraint of an unemployed worker $j = W, NW$ living in the area depends on his/her location, the transport mode and the information gathered about jobs in the employment center. In our framework, each unemployed commutes to the center to gather information about jobs. This is not the only way to obtain information since (see below) one can also obtain job information by buying newspapers or calling friends. However, each return trip from the residential location to the employment center allows the worker to have some additional information that is not accessible without going to the center (for example, looking at some ads that are locally posted or have interviews with employment agencies that are located in the center). What is crucial for the unemployed is their *job (or information) access* that is measured by both the *physical distance* to jobs and the *time distance* to reach the center (i.e. the trip time). For a worker $j = W, NW$, these two "distances" are related by the following relationship:

$$t_j = \frac{x_j}{\mu_j} \tag{1}$$

where x_j is the physical distance to jobs for a worker j, μ_j denotes the average trip speed (which crucially depends on the transport mode) and t_j is the time for *each return trip* to reach the employment center. Thus, if τ_j denotes the *pecuniary* cost per unit of physical distance to commute to the employment center and ϕ a positive constant, then for the unemployed workers the total cost per return trip of gathering information about jobs in the employment

12 percent households with no vehicles.

center is given by:[5]

$$\tau_j x_j + \phi\, t_j \tag{2}$$

In this formulation, there are two types of costs to commute to the center. The first one, $\tau_j x_j$, is the total *pecuniary* cost at a distance x_j and the second one, $\phi\, t_j$, is the *time* cost (even though this is not explicitly modeled, there is an opportunity cost of travelling because of the leisure forgone). We can now express this cost in the same unit. If it is expressed in terms of physical distance x_j, it is equal to:

$$\left(\tau_j + \frac{\phi}{\mu_j}\right) x_j$$

whereas, if it is expresses in terms of time distance t_j, it is given by

$$\left(\tau_j \mu_j + \phi\right) t_j$$

In this paper, we will focus on time distance rather than physical distance because we believe that job access is crucially determined by the former and not the latter. As a result, we will express all our relations in terms of t_j and when we write distance to jobs or job access it means time distance to jobs.[6] We can now determine the *total* cost at a distance $t_j$of gathering information about jobs in the employment center. It is given by:

$$\left(\tau_j \mu_j + \phi\right) t_j e_j \tag{3}$$

where e_j is the search effort provided by worker j. Obviously the higher e_j the more often the unemployed worker has to travel to the employment center to gather information about jobs. In this formulation, t_j is a measure of job access (how "well" the unemployed worker is connected to jobs) while e_j is a measure of search intensity (how many hours per day the unemployed worker spends in searching for a job).

If the individual *unemployment benefit* is denoted by b, then the instantaneous budget constraint of an unemployed worker j living at a distance t_j

[5]Observe that the transport-mode literature (see e.g. Sasaki, 1990) has mostly focussed on employed workers and thus this total cost has been written as

$$\tau_j x_j + \phi\, y_j\, t_j$$

where y_j is the income of worker j and is viewed as the opportunity cost of time since it varies with the number of working hours. Here we focus on unemployed workers and obviously there is no reason for the unemployment benefit to be affected by time cost.

[6]Observe that, since by (1) there is a one-to-one relationship between t_j and x_j, all our results in terms of t_j could be stated in terms of x_j.

from the employment center is equal to:

$$b = z_j + R(\mu_j t_j) + f_j + C(e_j) + \left(\tau_j \mu_j + \phi\right) t_j e_j \tag{4}$$

where z_j denotes the composite good consumption (which is taken as the numeraire) for a worker j, $R(\mu_j t_j)$, is the prevailing land rent per unit of land at each distance $x_j = \mu_j t_j$, f_j is the fixed cost of transportation and $C(e_j)$ denotes all searching costs that are not distance-related. The latter encompasses the costs of buying newspapers, making phone calls, ... We assume that $C(0) = 0$, $C'(e_j) > 0$ and $C''(e_j) > 0$. In this formulation, the total cost of searching is thus $C(e_j) + \left(\tau_j \mu_j + \phi\right) t_j e_j$, which encompasses both search costs that are not distance-related and costs that involve commuting to the employment center.

Our assumption that whites use cars and nonwhites public transportation implies that:[7]

$$f_W > f_{NW},\ \mu_W > \mu_{NW} \text{ and } \tau_W \mu_W < \tau_{NW} \mu_{NW} \tag{5}$$

i.e., cars used by whites have a higher fixed cost but are faster and entails smaller variable cost than public transportation.[8]

Let us now explain the macroeconomic environment in this area. Time is continuous. A vacancy can be filled according to a random Poisson process. Similarly, unemployed workers can find a job according to a random Poisson process. In aggregate, these processes imply that there is a number of contacts (or matches) per unit of time between the two sides of the market that are determined by the following standard matching function:

$$M \equiv M(\overline{s}u, v) \tag{6}$$

where u and v respectively denote the unemployment rate and the vacancy rate in the area, and $\overline{s}$ is the average search efficiency in the area (the average of both whites and nonwhites). In fact, each individual's search efficiency s_j

[7]We assume rather than derive transport mode choices because the aim of the theoretical analysis is not to study why workers choose different transport modes but to analyze the consequences of different transport modes on search behaviors. For models that derive transport mode choices, see for example LeRoy and Sonstelie (1983) and Sasaki (1990).

[8]Observe that the third part of the condition in (5) is expressed in terms of cost per unit of *time* distance. To express it in terms of cost per unit of *physical* distance, we would have to write:

$$\tau_W + \phi/\mu_W < \tau_{NW} + \phi/\mu_{NW}$$

depends on his/her effort e_j, i.e. $s_j \equiv s(e_j)$. We assume decreasing returns to scale to effort, i.e., $s'(e_j) > 0$ and $s''(e_j) \leq 0$.

As usual (Pissarides, 2000), $M(.)$ is assumed to be increasing in both its arguments, concave and exhibits constant returns to scale. As a result, the probability of obtaining a job per unit of time for an unemployed worker with search intensity $s_j \equiv s(e_j)$ is given by:

$$\frac{s(e_j)}{\overline{s}} \frac{M(\overline{s}u, v)}{u} = s(e_j)\, M\left(1, \theta\right) \tag{7}$$

where $\theta = v/(\overline{s}u)$ is a measure of labor market tightness in search intensity units. By using the properties of the matching function, it is easy to see that

$$\frac{\partial M\left(1, \theta\right)}{\partial \theta} > 0 \tag{8}$$

since more vacancies increase the probability to find a job.

All workers are assumed to be risk neutral and infinitely lived. If one denotes the *unemployed state* for workers by '0', and the *employed state* by '1', then W_j^0, the expected discounted lifetime utility of an unemployed worker j living at a distance x_j from the employment center is, in steady-state, given by:

$$rW_j^0 = b - R(\mu_j t_j) - f_j - C(e_j) - \left(\tau_j \mu_j + \phi\right) t_j e_j + s(e_j) M\left(1, \theta\right) \left(W_j^1 - W_j^0\right) \tag{9}$$

where $r \in (0, 1)$ is the discount rate and W_j^1 the expected discounted lifetime utility of an employed worker j living at a distance t_j from the employment center. In this formulation, if someone obtains a job, he/she remains in the same location. Equation (9) has a standard interpretation. When a worker is unemployed today, he/she obtains an instantaneous (indirect) utility equals to $b - R(\mu_j t_j) - f_j - C(e_j) - \left(\tau_j \mu_j + \phi\right) t_j e_j$. Then, he/she can get a job with a probability $s(e_j) M\left(1, \theta\right)$ and, if so, obtains an increase in utility of $W_j^1 - W_j^0$.

2.2 Search intensity within each race

Let us now study the search effort decision for each type of worker. In other words, we would like to analyze the search decision within each race (white and nonwhite) and examine how s_j is related to job access t_j.

When making the search effort decision e_j, the unemployed worker j takes as given the unemployment level u in the area where he/she lives, the local number of vacancies (and thus $\theta = v/\overline{s}u$, the local labor market tightness), the local land rent and the expected discounted lifetime utilities W_j^0 and W_j^1. By maximizing (9) with respect to e_j, we obtain[9]

$$\frac{\partial W_j^0}{\partial e_j} = -C'(e_j^*) - \left(\tau_j \mu_j + \phi\right) t_j + s'(e_j^*) M\left(1, \theta\right) \left(W_j^1 - W_j^0\right) = 0 \qquad (10)$$

where e_j^* is the unique solution of this maximization problem and $s_j^* \equiv s(e_j^*)$ is the corresponding optimal search efficiency.

Let us give the intuition of (10). When choosing e_j^*, there is a fundamental trade-off between short-run and long-run benefits for an unemployed j located at a distance t_j from the center. On the one hand, increasing search effort e_j to gather more information about jobs is costly in the short run (today) because it decreases instantaneous utility, $-C'(e_j^*) - \left(\tau_j \mu_j + \phi\right) t_j < 0$, so that the worker consumes less quantity of the composite good (budget constraint). On the other hand, increasing search effort e_i increases the long-run (tomorrow) prospects of employment since it increases the probability to obtain a job $s'(e_j^*)M\left(1, \theta\right) > 0$ and the surplus $W_j^1 - W_j^0$ associated with it.

Since, within each race, all workers are identical, they all choose the same effort level e_j^* and thus the average effort level $\overline{e}_j^*$ is equal to the individual search effort, i.e. $\overline{e}_j^* = e_j^*$. The average search efficiency of each type of worker is thus given by $\overline{s}_W = s(\overline{e}_W)$ and $\overline{s}_{NW} = s(\overline{e}_{NW})$.

Let us state our first result.

Proposition 1 (Job access) *For both whites and nonwhites, the worse the access to jobs (i.e. the higher time distance), the lower the individual and average search intensity.*

Proof. See Appendix 1.

This result shows that, if unemployed workers have bad access to jobs (there are "far away" in terms of time distance), then they will search less than those who have a better access because *it takes more time (and it thus more costly) to gather information about jobs.* In other words, if we control for transportation mode (i.e. we fix μ_j and τ_j) and thus focus on the search behavior of whites and nonwhites separately, then this proposition says that remote locations

[9]It is easy to verify that the second order condition is always satisfied since it is given by:

$$-C''(e_j) + s''(e_j) M\left(1, \theta\right) \left(W_j^1 - W_j^0\right) < 0$$

reduce search intensity for any worker, i.e. $\overline{s}'_j(t_j) < 0$, $j = W, NW$. It is easy to see in Appendix 1, that this relationship between $\overline{s}_j$ and t_j is non-linear.

This proposition is basically giving a theoretical mechanism for the spatial mismatch. By fixing transport mode, we are able to only see the impact of job access on search intensity.

This result is related to that of Smith and Zenou (2003). Indeed, in the latter, distance to jobs reduces search effort not because of higher time cost to obtain information about jobs but because of lower land rent and thus lower cost of being unemployed. More precisely, Smith and Zenou (2003) show that housing prices are very low at a distance from jobs, and thus unemployed workers feel less pressure to find a job in order to pay their rent. As a result, they tend to search less.

Another related mechanism has been proposed by Wasmer and Zenou (2002, 2003). They show that the efficiency of job search decreases with distance to jobs because workers obtain less information about distant job opportunities; in particular because firms resort to local recruiting methods (such as ads in local newspapers or wanted signs) that exclude distant workers.

We believe that these three mechanisms that explain why distance to jobs reduces search intensity (higher costs of gathering information, lower housing prices, reduced information about jobs) are complementary. Empirically, Davies and Huff (1972) have shown that workers search more efficiently in a closer area (better integrated labor market) while Seater (1979) has shown that workers searching further away from the residence are less productive than those who search closer to where they live. Barron and Gilley (1981) and Chirinko (1982) have also shown that there are diminishing returns to search when people live far away from jobs. Finally, Rogers (1997) has demonstrated that access to employment is a significant variable in explaining the probability of leaving unemployment.

2.3 Search intensity between races

We would like now to compare workers of difference races who have exactly the same access to jobs, i.e. the same time distance $t_{NW} = t_W = t$. In other words, if we take two workers, one white and one nonwhite, located at exactly the same time distance t from the employment center and who differ only by their transportation mode, which one will provide the higher search effort? The following proposition provides a clear answer to this question.

Proposition 2 (Transport mode) *Assume that nonwhites use public transportation to commute to the center while whites use private vehicles. If we compare a white and a nonwhite unemployed worker who have exactly the same access to jobs (i.e the same time distance), then the white unemployed worker will search more intensively than the nonwhite.*

Proof. See Appendix 1.

This proposition is in some sense the dual of Proposition 1. Indeed, instead of fixing μ_j and τ_j and see the impact of different job access on search intensities (Proposition 1), we here fix job access t_j and evaluate the impact of different transport modes on search decisions.

If we are comparing white and nonwhite workers who both live exactly at the same time distance to the employment center, then because whites use a private transport mode, they do have a lower variable commuting cost of (time) distance, i.e. $\tau_W \mu_W < \tau_{NW} \mu_{NW}$ (see (5)). As a result, it is less costly for whites to gather information about jobs and thus they search more intensively than nonwhites.

In this proposition, by fixing job access, we are able to only see the impact of transport mode on search intensity. Raphael and Stoll (2001) find that raising minority car-ownership rates to the white car ownership rate would considerably narrow inter-racial employment rate differentials. Similarly, Raphael and Rice (2002) show that there is a positive relationship between car ownership and employment outcomes.

We have finally the following result.

Corollary 1 (Job access and transport mode) *Assume that nonwhites use public transportation to commute to the center while whites use private vehicles. Assume also that nonwhites have a worse job access than whites. Then, their search intensity is lower than whites.*

This corollary is a straightforward extension of the two previous propositions. It is consistent with empirical studies. In particular, Holzer *et al.* (1994) found that blacks not only have longer travel times to work but also cover less distance while searching. As in our model, this implies that the time cost per mile traveled is thus substantially higher for blacks than for whites. They also find that the higher time cost is partly accounted for by the lower rates of car ownership among blacks.

Let us now see if this model passes the test of the data. Of course, in the real-world, a small fraction of nonwhites use cars and a small fraction of whites use public transportation (see the figures given at the beginning of section 2). It should however be clear that all our theoretical results are still valid if a small fraction of nonwhites use cars (as it is the case in the real-world) as long as this fraction is lower than the percentage of whites using cars.

3 Data and statistical model

The aim of the empirical analysis is to test the two propositions and the corollary of the theoretical model (propositions 1 and 2 and corollary 1). The first one states that, within a race, the worse the job access, the lower the search intensity of the unemployed. Controlling for transport mode, we are basically testing the spatial mismatch hypothesis and expect that, for each race, worse job access leads to lower search intensities. The second one compares white and nonwhite workers assuming that the former use private vehicles and the latter public transportation, and shows that, with exactly the same job access, white workers search more actively than nonwhites. The theoretical explanation of this result is empirically supported if whites' and nonwhites' search intensities are positively affected by whites' and nonwhites' access to a private transport mode respectively. Finally, corollary 1 would be verified if *both* job access and car access have a positive and significant effect on search intensity.

3.1 Data

Our empirical analysis is based on NUTS3 level data in England.[10] The main data source is the Labour Force Survey (LFS hereafter).[11] Given an area, the key variables under investigation are the (average) search intensity, the

[10]The Nomenclature of Territorial Units for Statistics (NUTS) was established by the Statistical Office of the European Communities (Eurostat) to provide a single, uniform breakdown of territorial units for the production of Community regional statistics. In Britain, NUTS3 administrative areas are smaller than counties. For example, in the metropolitan area of London, there are five NUTS3 areas.

[11]Because of small sample sizes per area for ethnic minority groups (nearly half of Britain's minority ethnic population lives in London (Fieldhouse, 1999) and London has been excluded of our analysis; see footnote 14), we combine the autumn quarters of the LFS for 2000, 2001 and 2002 to derive information on white-nonwhite differentials in search behavior, commuting time and car access. Sample size problems also prevent us to carry out an analysis that distinguishes between different ethnic minority groups (nonwhites include all ethnic minorities: black Caribbeans, Indians, Pakistanis, African-Asians, Bangladeshis and Chineses) and between different categories (i.e. separating by gender, age, education).

(average) access to jobs and the (average) access to a private mode of transportation.

We define the average white (nonwhite) search intensity in an area, $\overline{s}_W$ ($\overline{s}_{NW}$), as the ratio between white (nonwhite) active job seekers, and the sum of white (nonwhite) active job seekers and white (nonwhite) inactive persons living in the area.[12] Observe that, in order to obtain a variable capturing a positive behavior of jobless people in the search process, our definition of active job seekers (the numerator in our measure of local search intensity) includes both the unemployed (these are job seekers who are immediately available for a job) and the persons who declare themselves as job seekers but are currently unavailable to start working (thus defined inactive according to the standard ILO definition of economic activity) for no valid reason.

In the empirical spatial-mismatch literature, the measure of job access is obviously crucial (see in particular the survey by Ihlanfeldt and Sjoquist, 1998). In fact, the job access measure has been constructed at different levels of aggregation of the data: individual level (Ihlanfeldt and Sjoquist, 1990), neighborhood level (Raphael, 1998) and metropolitan level (Weinberg, 2000).

Our measure of job access is calculated at a rather aggregate level, NUTS3 area, to avoid an endogenous sorting into neighborhoods. It is based on *actual daily two-way travel-to-work time of the employed workers in a NUTS3 area.*[13] The LFS asks about the usual residence to work travel time in minutes and the usual method of transport (only asked in the autumn quarter). We define the average white (nonwhites) commuting time in an area, $\overline{t}_W$ ($\overline{t}_{NW}$), as the ratio between the total time spent travelling to jobs by the employed whites (nonwhites) workers living in the area, and the total number of employed whites (nonwhites) workers in the area. In short, our proxy of time distance to jobs for an unemployed worker living in an area is the average commuting time of the employed workers living in the same area. In conformity with our theoretical model, we define race-specific measures of job access because of the different transport mode used by whites and nonwhites.

Finally, our last key variable is transport mode. We measure the average

[12]The ideal variable to measure search effort would have been, at the individual level, the number of hours spent looking for a job. Unfortunately, this variable is not available in any British survey. This is why we resort to our aggregate indicator of search intensity and, as a result, all our empirical analysis will be conducted at an aggregate level (i.e. NUTS3 area).

[13]Some papers have used a similar job access measure for the US: "the mean commuting time of workers who live nearby". See in particular Ihlanfeldt and Sjoquist (1990), Ihlanfeldt (1992), and Kasarda and Ting (1996)

white (nonwhite) access to a private mode of transportation (indicated hereafter as car access) in an area, $\overline{c}_W$ ($\overline{c}_{NW}$), by the number of white (nonwhite) active job seekers owning or using a motor vehicle divided by the total number of whites (nonwhites) active job seekers.[14]

The underlying assumptions are that whites and nonwhites do not use on average the same transport mode and that employed and unemployed whites (nonwhites) use the same transport mode (the former to travel to work and the latter to search for a job). Indeed, these assumptions appear to be supported by the data. In our data base, the percentage of whites and nonwhites using coach, bus or British rail train to travel to work is 15% and 40.2% respectively and the percentage of whites and nonwhites using car or scooters is 79.1% and 57.7% respectively. On the other hand, the percentage of white and nonwhite active job seekers owning or using a motor vehicle is 75.8% and 55.4% respectively.[15] In other words, it is plausible to assume that whites use mainly private transport, nonwhites mainly public transport and that white (nonwhite) unemployed's private transport mode is similar to that of white (nonwhite) employed.

In order to control for differences in skill composition, quality of unemployed, population structure, economic activity, sectorial composition, income and wealth, cost of living, labor market conditions, ethnic composition, agglomeration effects, social networks among NUTS3 areas, we include as regressors in our empirical model indicators of education, percentage of long-term unemployed, economic activity, employment by occupation, indices of earnings by occupation and home ownership, an index of house prices, the tightness of the local labor market, ethnicity, population density, main method of job search of job seekers living in the area respectively.[16]

[14]We are aware that car access is a tricky variable because it has an endogenous component. We try to control for that by including a variable that captures the "quality of the workers", namely the percentage of long-term unemployed in the area.

[15]Since differences in transport modes are the key factors driving our theoretical results, we have excluded London from our sample because, in London, most workers use public transportation (especially the tube) and thus, according to our model, the main difference between whites and nonwhites disappears. We have in fact done the same analysis for London only and for all England including London and found that, in both cases, car access and distance to jobs had no significant impact on search intensity.

[16]Because the LFS sub-regional data are made available only starting from spring 2000 and earnings data are only available until year 2000, all the control variables are year 2000 annual averages. All data can be obtained on line from the NOMIS database run by the University of Durham (on behalf of the Office for National Statistics) or in the ESRC Data Archive with the exception of house prices, that are available on line from the HM Land

In order to avoid that differences in earnings across areas are due to the composition of the labor force in the areas, we use a fixed weight index of earnings. Similarly, in order to avoid that differences in house prices across areas are due to different types of houses being sold in the areas, we also use a fixed weight house prices index. The construction of both indices is detailed in Appendix 3. Appendix 5 contains the list of the 85 NUTS3 administrative areas considered in the analysis.[17] Precise definitions of all variables used in the empirical analysis can be found in Appendix 2.

Table 1 contains the summary statistics. First, not surprisingly, the mean daily commute is lower for whites than for nonwhites. This is consistent with most of the American studies (see e.g. Chung et al. 2001, and Gottlieb and Lentnek, 2001) and is mainly due to the fact that nonwhites are in general further away from jobs than whites and use slower transport mode (mainly public transportation). Second, whites seem to search more intensively than nonwhites. Finally, 75.8% of the unemployed white workers have access to a car whereas this number is only 55.4% for the nonwhites.

[*Insert Table* 1 *here*]

3.2 Statistical model

Our empirical strategy is to investigate to what extent differences in search intensities among job seekers is related to job access (time distance to jobs) and different transport modes (races), once the influence of other area specific characteristics (tightness of the local labor market, local cost of living, income and wealth, qualifications, quality of the unemployed, occupational, ethnicity and population structures, activity rates, social networks, agglomeration) and spatial spillovers effects have been controlled for. Basically, in order to validate empirically the theoretical implications of our model, we should obtain that, within a race (white or nonwhite), average search intensity decreases with job access, i.e. average commuting time of the employed (Proposition 1), and, between races, for the same job access, whites search more actively than nonwhites (Proposition 2). Furthermore, both whites and nonwhites search effort should be positively influenced by having access to a private vehicle and distance to jobs (Corollary 1).

In Appendix 4, we show that the appropriate model to be estimated is a

Registry.

[17] Some NUTS3 areas have been aggregated due to lack of data on some of the variables.

spatial lag model (instead of a standard model without spatial lag and instead of a spatial error model).[18] As a result, in our empirical analysis, we use the following mixed regressive spatial autoregressive model[19]

$$y = \rho P y + X\beta + \varepsilon \tag{11}$$

where y is a $N \times 1$ vector of observations on the dependent variable, Py is a $N \times 1$ vector of spatial lags for the dependent variable that is based on the value of neighboring observations, ρ is the spatial autoregressive coefficient, X is a $N \times k$ matrix of observations on the explanatory variables associated with a $k \times 1$ vector of regression coefficients β and ε is a $N \times 1$ vector of normally distributed random error terms, with means 0 and constant variances σ^2. We define the spatial lags for the dependent variable, Py, as the average value of the dependent variable over the areas that share a common boundary with area i. This is obtained by setting the elements of the matrix P, p_{ij}, equal to 0 if $i = j$ or if i and j are not adjacent, and equal to a constant otherwise (defined by imposing the normalization $\sum_{j=1}^{n} p_{ij} = 1$ for each i).[20]

This regression model with a spatially lagged dependent variable can be estimated by Maximum Likelihood (ML)[21] and it can be used for two different purposes. If the main empirical interest consists of investigating spatial effects, then one can consider the inclusion of a spatially lagged dependent variable in addition to other explanatory variables as a way to assess the degree of spatial dependence, while controlling for the effects of these other variables. Alternatively, the inclusion of a spatially lagged dependent variable allows us to assess the significance of the other (non-spatial) variables, after the spatial dependence is controlled for. This latter strategy is the one pursued in our analysis. Our aim is *to estimate the impact of job access and car access on*

[18]One may argue that, from an economic point of view, a *spatial error model* may be more justified than a *spatial lag model* since spatial correlation in search intensity is more likely to arise from spatially correlated unobservable factors and/or omitted variables. For robustness check, we have conducted the same empirical analysis using a spatial error model. All our main results, i.e. the positive and significant effect of distance to jobs and car access on search intensity, the shape of the estimated distance function (Figures 1 and 2) and the relative stronger impact of car access on the difference in search intensity between whites and nonwhites, are qualitatively the same. These results are available upon request.

[19]Theoretical details on the autoregressive simultaneous model with the inclusion of vectors of exogenous variables can be found, among others, in Anselin (1988).

[20]The $N \times N$ matrix $P = \{p_{ij}\}$ is sometimes called contiguity matrix in the spatial statistics literature. It describes the geographical arrangement of the spatial units.

[21]For further details on the adaptation of the Maximum Likelihood estimator to the spatial case and on the estimation procedure see, among others, Anselin (1988).

search effort, once spatial effects and the influence of other variables have been filtered out.

4 Empirical results

In accordance with our theoretical model, we undertake two types of analyses. In the first one, we investigate the impact of search intensity on job access and mode choice for each race separately. In the second one, we analyze the impact of job-access and mode-choice differences between whites and nonwhites on search-intensity differences. In particular, using a partial decomposition analysis (Oaxaca, 1973), we evaluate the relative importance of car access and distance to jobs on search intensity differences between races.

4.1 Separate estimations by race

Because different variables may affect differently the behavior of whites and nonwhites in the labor market, we estimate the econometric model defined by equation (11) separately for whites and nonwhites. The only differences in the specification of the model in the two cases are in the definition of the dependent variable ($\overline{s}_W$ and $\overline{s}_{NW}$ respectively), of the measure of job access ($\overline{t}_W$ and $\overline{t}_{NW}$ respectively) and of the measure of car access ($\overline{c}_W$ and $\overline{c}_{NW}$ respectively). The other control variables related to the local area where job seekers live are common to both specifications.

In order to understand in depth the relationship between commuting time and search effort and to be able to capture empirically any differences in search effort decisions between whites and nonwhites, following the result of our theoretical model, we estimate the following *non-linear* commuting time function:

$$f(\overline{t}) = \frac{\alpha}{\overline{t}} + \frac{\gamma}{\overline{t}^2} \tag{12}$$

where $\overline{t}$ is replaced by $\overline{t}_W$ ($f_W(\overline{t})$) and $\overline{t}_{NW}$ ($f_{NW}(\overline{t})$) in the model for whites and nonwhites respectively. The underlying assumption is that search effort goes to 0 when commuting time tends to infinity. Once the parameters α and γ are estimated in a model that takes into consideration the influence on search effort of other possible relevant variables and unobservable (spatial) effects, any difference in the shape of the estimated function $f(\overline{t})$ for whites and nonwhites should reflect differences in search effort decisions due to factors related to employed workers' commuting time (proxy for distance to jobs).

For sake of clarity, we rewrite equation (11) by separating the race-specific variables from the other control variables, and by separating whites and nonwhites. We obtain respectively

$$\overline{s}_W = \rho P \overline{s}_W + \frac{\alpha}{\overline{t}_W} + \frac{\gamma}{\overline{t}_W^2} + \delta \overline{c}_W + X\beta + \varepsilon \tag{13}$$

and

$$\overline{s}_{NW} = \rho P \overline{s}_{NW} + \frac{\alpha}{\overline{t}_{NW}} + \frac{\gamma}{\overline{t}_{NW}^2} + \delta \overline{c}_{NW} + X\beta + \varepsilon \tag{14}$$

Table 2 reports the Maximum Likelihood estimation results for these two models, defined for whites by (13) and for nonwhites by (14), in the second and fourth columns respectively. For comparison purpose, the first and third columns of this table display the OLS estimates that are obtained by estimating the two equations (13) and (14) without the inclusion of a spatially lagged dependent variable.[22]

Table 3 has the same structure of Table 2 (results for the spatial lag model in the second and fourth columns and for the classical regression model in columns one and three for whites and nonwhites respectively) and it reports measures of fit and hypotheses tests. In Appendix 4, we analyze in details these regression diagnostics. We conclude that the spatial lag models defined by (13) and (14) appear to be appropriate and correctly specified.

Let us now focus our attention on the interpretation of the Maximum Likelihood estimation results for model (13) and (14) (column two and four of Table 2 respectively). Firstly, having access to a car increases search intensity for both whites and nonwhites (estimate of δ positive and significant at 1% level) in both models (13) and (14). This finding confirms the key role of transport mode in shaping job seekers search effort decisions.

Secondly, the estimated coefficient α of $1/\overline{t}$ is positive and significant for both whites and nonwhites. In accordance with the predictions of our theoretical model, in particular Proposition 1, this means that, after controlled for average levels of education, earnings, ... in each area i, *within each race, a higher average commuting time of the employed living in area i, i.e. a worse job access for the unemployed living in the same area, leads the unemployed to search less intensively.* Our interpretation of these results is that, controlling for the transport mode (since the estimation is done separately for each race), higher commuting time for the employed implies that the unemployed workers

[22]All the estimation results have been obtained using SpaceStat version 1.80 (Anselin, 1995).

are not well connected to jobs so that information about jobs is quite costly to obtain. As a result, those workers will search less than those residing in areas better connected to jobs.

Among the control variables, quite intuitively, the search behavior of whites' job seekers living in an area appear to be positively and significantly affected by the activity rate, the percentage of young people, the cost of living, the tightness of the labor market in the area and negatively and significantly by the percentage of old people and by the percentage of long-term unemployed in the area. On the other hand, the search behavior of nonwhites' job seekers living in an area appears to be affected in the same way by the same variables, with the exception of the percentage of long-term unemployed, whose estimated coefficient is now positive and significant. It is also positively and significantly affecte by the percentage of employed people in manual and elementary occupation (SOC 8,9), by the index of earnings for the same occupational group (SOC 8, 9) and negatively and significantly by the percentage of whites people living in the area and by our proxy of social networks. Interestingly, these empirical results provide some evidence suggesting that nonwhites are mainly low skilled workers scarcely integrated in the local social networks schemes. Also, the opposite impact of the percentage of long-term unemployed between white and nonwhite search intensity (negative and positive respectively) may indicate that nonwhites tend to search more in areas where employment opportunities are low, whereas whites tend to search in areas where there are high.

[*Insert Tables* 2 *and* 3 *here*]

The estimated functions of commuting time (12) for whites and nonwhites are plotted in Figures 1a and 1b. The two diagrams show the influence of job access ($\overline{t}_W$ and $\overline{t}_{NW}$ for whites and nonwhites respectively) on search intensity *purged* by the effects of the other control variables (denoted by $\overline{s}_W^p$ and $\overline{s}_{NW}^p$ for whites and nonwhites respectively).[23] The diagrams are in the same scale.

These two curves present the following interesting feature. For both whites and nonwhites, within each race, the unemployed workers' average search in-

[23]From the estimation of model (13) and (14) we define

$$\overline{s}_W^p = \overline{s}_W - \rho P \overline{s}_W - \delta \overline{c}_W - X\beta = \frac{\alpha}{\overline{t}_W} + \frac{\gamma}{\overline{t}_W^2}$$

and

$$\overline{s}_{NW}^p = \overline{s}_{NW} - \rho P \overline{s}_{NW} - \delta \overline{c}_{NW} - X\beta = \frac{\alpha}{\overline{t}_{NW}} + \frac{\gamma}{\overline{t}_{NW}^2}$$

for whites and nonwhites respectively.

tensity is a decreasing function of their job access (as measured here by the average commuting time of the employed). This is exactly the prediction of Proposition 1 and it is conformed to the spatial mismatch hypothesis: the worse the job access, the lower search activities.

[*Insert Figures* 1*a and* 1*b here*]

In order to see more precisely the validity of Proposition 2, in Figure 2, we have put together these two curves in the same diagram. The result is striking: for a given time distance to jobs and controlling for car access within race, white unemployed workers search more intensively than nonwhite unemployed workers. We propose a posible interpretation of this result based on differences in transport modes. Indeed, in accordance with our theoretical model, if both white and nonwhite unemployed workers live in areas where the average commuting of the employed is, say, 30 minutes (i.e. same time distance to jobs), then whites will search more actively than nonwhites because, using private transport, it is less costly for them to gather information about jobs. As already noted, the importance of transport mode in shaping job seekers search decisions is empirically validated by the positive and significant estimate of the coefficient of the car ownership-usage ratio (δ) in both model (13) and (14).

Certainly, this difference in search intensity is also due to unobservable factors (such as workers' ability and discrimination). In the next section, we show that 18.3 percent of the racial gap remains unexplained.

[*Insert Figure* 2 *here*]

4.2 Inter-race differences

The significant effects of white (nonwhite) average (time) distance to jobs and car access on white (nonwhite) search intensity suggest that part of the ethnic differences in search rates can be attributed to differences in these race-specific variables.

We now use partial decomposition analysis (Oaxaca, 1973) to measure this contribution, that is the proportion of ethnic differences in search rates that can be explained by white-nonwhite differences in (time) distance to jobs and car access.[24] We also estimate the relative importance of each of them in shaping inter-race search intensity differentials, that is we estimate the proportion of

[24]See for example Stoll and Raphael (2000) for an application of this tehnique to measure the contribution of spatial job search quality to racial employment differences in the US.

ethnic differences in search rates that can be explained by white-nonwhite differences in (time) distance to jobs and car access separately.

Using the estimation results from model (14), we estimate the predicted nonwhite search intensity $\widehat{s}_{NW}$ when the nonwhite mean (time) distance to jobs and car access (or only one of the two variables) are substituted by those observed for white workers. The difference between the mean observed white search rate and the predicted nonwhite search rate is then compared to the actual white-nonwhite difference in search rates.

Table 4 presents the results of this decomposition. As can be seen, giving to nonwhite workers the mean level of white (time) distance to jobs and white car access would close the racial gap in search intensity by 39.2 percent. Indeed, quite a substantial proportion of the mean white-nonwhite difference in search rates can be explained by differences in these race-specific variables. Even more interesting, we find that the gap would be closed by 31.5 percent only by raising nonwhite car access rate to the white's one.

Inter-race differences in (time) distance to jobs account only for 7.7 of the disparity between white and nonwhite search intensities. This support the crucial role played by transport mode in the theoretical model. This has crucial implications for policy makers. It suggests that subsidizing car ownership for the unemployed ethnic minority in England could have a substantial impact on their search activity and thus on their unemployment rate. This is a standard policy that has been advocated in the US (see e.g. Pugh, 1998) but rarely emphasized in England.

[*Insert Table* 4 *here*]

Our results are in fact quite similar to the ones established in the US. For example, Stoll (1999) shows that increasing blacks' and Latinos' access to cars or decreasing their average distance to search areas will lead to greater geographic job search. Raphael and Stoll (2001) found that raising minority car-ownership rates to the white car ownership rate would considerably narrow inter-racial employment rate differentials.

Finally, for completeness, the last two rows of Table 4 report (*i*) the percentage of racial gap explained by observable variables (population's differences in observed characteristics included in the model, i.e. in the spatial average of search rates, distance to jobs and car access) and (*ii*) the percentage due to unobservable factors (such as workers' ability and discrimination).[25] The

[25]Note that this part may also include the effects of omitted variables.

figures are 81.7 percent and 18.3 percent respectively.[26] As it is apparent in Figure 2, there is a fair portion of the race gap in search rate left unexplained.

5 Conclusion

This paper has shed some light on the link between job access, transport mode and search activity rates in the UK. In the first part, we have tried to better understand the mechanism that drives the spatial mismatch hypothesis (which supports the view that because nonwhite workers reside in zones that are distant and poorly connected to major centers of employment, they are confronted to barriers in the finding of well-paid jobs) by providing a transport-mode-based theory. We have shown that, for both whites and nonwhites, longer time distance to jobs leads to lower search effort because it takes more time (and it thus more costly) to gather information about jobs. We have also shown that, because of different transport modes, at exactly the same time distance to jobs, white unemployed workers search more intensively than nonwhites. This is because whites use a different transport mode and thus can reach the center at a lower cost and, as a result, can gather more information about jobs than nonwhites.

In the second part of the paper, we have tested this theoretical model using English data. Our job access variable is based on actual daily two-way travel-to-work time of the employed workers in an area. We have shown that, indeed, living in areas where employed workers' average commuting time is higher yield the unemployed to search less than in areas with lower commuting time. We have also shown that having access to a car increases search intensity for both whites and nonwhites and that, for a given job access, unemployed whites search more intensively than unemployed nonwhites. Our final results provide strong evidence that differences in search activities between whites and nonwhites are due to differences in job access as well as differences in car ownership. In particular, having access to a car has a stronger effect on the racial gap in search intensity than distance to jobs.

[26] These values are obtained using a traditional Oaxaca decomposition. Parts (i) is calculated by multiplying the white (nonwhite) coefficients estimates by the white-nonwhite differences in the corresponding mean variables and (ii) by multiplying the white-nonwhite differences in the estimated coefficients by the nonwhite (white) mean variables.

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Appendix 1: Proofs related to the theoretical model

Proof of Proposition 1

By totally differentiating (10), we obtain:

$$\frac{\partial e_j^*}{\partial t_j} = \frac{\tau_j \mu_j + \phi}{SOC} < 0$$

where

$$SOC \equiv -C''(e_j) + s''(e_j) M\left(1, \theta\right) \left(W_j^1 - W_j^0\right) < 0$$

Furthermore, since $s_j \equiv s(e_j)$, with $s'(e_j) > 0$, then

$$\frac{\partial s_j^*}{\partial t_j} < 0$$

Finally, since $\overline{e}_j = e_j$ and $\overline{s}_j = s(\overline{e}_j)$, with $s'(\cdot) > 0$, then

$$\frac{\partial \overline{e}_j^*}{\partial t_j} < 0 \text{ and } \frac{\partial \overline{s}_j^*}{\partial t_j} < 0$$

■

Proof of Proposition 2

We want to compare a white and a nonwhite unemployed worker located at exactly the same time distance, i.e. $t_{NW} = t_W = t$. It is easy to see from (10) that the main difference between these two workers is the variable cost. But since by (5), $\tau_W \mu_W < \tau_{NW} \mu_{NW}$, then obviously the optimal effort level of nonwhites will be lower than that of whites, i.e. $e_{NW}^* < e_W^*$. Another way to see that is to totally differentiating (10). We obtain:

$$\frac{\partial e_j^*}{\partial (\tau_j \mu_j)} = \frac{t}{SOC} < 0$$

where

$$SOC \equiv -C''(e_j) + s''(e_j) M\left(1, \theta\right) \left(W_j^1 - W_j^0\right) < 0$$

This says that, if we fix t, the higher $\tau_j \mu_j$, the lower search effort e_j^*. If we now aggregate the behavior, then this implies that $\overline{e}_W^* > \overline{e}_{NW}^*$ and $\overline{s}_W^* > \overline{s}_{NW}^*$.

■

Appendix 2: Description of variables

$\overline{s}_W(\overline{s}_{NW})$: Ratio between white (nonwhite) unemployed and job seekers currently unavailable to start working without a valid reason, and white (nonwhite) unemployed, job seekers currently unavailable and inactive persons. Source: LFS-INECA variable. It is a derived variable which classifies the individual economic activity according to the ILO standard definitions.

$\overline{t}_W(\overline{t}_{NW})$: Ratio between total time spent travelling to jobs by white (nonwhite) employed workers, and total number of white (nonwhite) employed. Source: LFS

$\overline{c}_W(\overline{c}_{NW})$: Ratio between white (nonwhite) active job seekers owning or using a motor vehicle, and total number of white (nonwhite) active job seekers. Source: LFS.

a: ratio between men of working age economically active and men of working age (16-64). Source: LFS (available from NOMIS).

$skills3+$: ratio between economically active men above NVQ2 (NVQ3, NVQ4 and higher) and with other qualifications and men of working age economically active. Source: LFS (available from NOMIS).

$y16-24$: Men aged 16-24 over men aged more than 16. Source: LFS (available from NOMIS).

$y25-49$: Men aged 25-49 over men aged more than 16. Source: LFS (available from NOMIS).

$y50-64$: Men aged 50 up to retirement age over men aged more than 16. Source: LFS (available from NOMIS).

e_123: All in employment working as managers, professional and technical occupations (SOC 1,2,3) over total number of employed. Source: LFS (available from NOMIS).

e_67: All in employment working as personal service, sales and customer service occupations (SOC 6, 7) over total number of employed. Source: LFS (available from NOMIS).

e_89: All in employment working as process, plant and machine operatives and other elementary occupations (SOC 8, 9) over total number of employed. Source: LFS (available from NOMIS).

$whites$:White men aged more than 16 over total men aged more than 16. Source: LFS (available from NOMIS).

$network$: men job seekers of working age that use friends and relatives as main method of job search over total number of men job seekers of working age. Source: LFS (available from NOMIS).

θ: Ratio between monthly unfilled vacancies and unemployed. Source: NOMIS.

h_ow: persons home owners over persons aged more than 16. Source: LFS.

h: Index (fixed weight) of house prices (construction detailed in Appendix 3). Source: HM Land Registry.

w_123: Index (fixed weight) of earnings for managers, professional and technical occupations (SOC 1,2,3) (construction detailed in Appendix 3). Source: New Earnings Survey (available from NOMIS).

w_45: Index (fixed weight) of earnings for administrative, secretarial occupations and skilled trades (SOC 4, 5) (construction detailed in Appendix 3). Source: New Earnings Survey (available from NOMIS).

w_67: Index (fixed weight) of earnings for personal service, sales and customer service occupations (SOC 6, 7) (construction detailed in Appendix 3). Source: New Earnings Survey (available from NOMIS).

w_89: Index (fixed weight) of earnings for process, plant and machine operatives and other elementary occupations (SOC 8, 9) (construction detailed in Appendix 3). Source: New Earnings Survey (available from NOMIS).

d: Density: ratio of residents over squared hectometers. Variable taken from the 1991 Census database and updated using the Midyear Population Estimates. Source: NOMIS.

un_dur: Ratio between unemployed for more than six months and total number of unemployed. Source: LFS.

Appendix 3: Index (fixed weight) of earnings and house prices

We consider four indices of earnings (listed in Appendix 2) that are based on the major groups of the Standard Occupational Classification (SOC2000). They are constructed as follow.

Index (fixed weight) of earnings for area i and group q:

$$I_{iq} = \frac{\sum_{j=1}^{Q} w_{ij}\overline{\eta}_j}{\sum_{j=1}^{Q} w_{UKj}\eta_{UKj}}, \qquad q = 1, ..., 4$$

where Q is the number of occupational sub-groups j in each group q, and

$$\overline{\eta}_j = \frac{\eta_j}{\eta_{UK}},$$

$$\begin{aligned} \eta_j &= \text{employed in sub group } j \text{ in UK}, \\ \eta_{UK} &= \text{total employed in UK}, \\ w_{ij} &= \text{average hourly wage of employed in sub group } j \text{ in area } i, \\ w_{UKj} &= \text{average hourly wage of employed in sub group } j \text{ in UK}. \end{aligned}$$

Similarly, the house price index is constructed as follow.

Index (fixed weight) of house prices for area i:

$$I_i = \frac{\sum_{j=1}^{Q} P_{ij}\overline{\eta}_j}{\sum_{j=1}^{Q} P_{UKj}\eta_{UKj}},$$

where Q is the number of types of houses (detached, semidetached, terrace), and

$$\overline{\eta}_j = \frac{\eta_j}{\eta_{UK}},$$

$$\begin{aligned} \eta_j &= \text{sales of houses of type } j \text{ in UK}, \\ \eta_{UK} &= \text{total sales of houses in UK}, \\ P_{ij} &= \text{average price of houses of type } j \text{ in area } i, \\ P_{UKj} &= \text{average price of houses of type } j \text{ in UK}. \end{aligned}$$

Appendix 4: Regression diagnostics

In this appendix we provide evidence that the two statistical models defined by (13) and (14) are appropriate and correctly specified.

Let us consider Table 3. The first row reports the maximized log likelihood (LIK) and the second and third row contain two likelihood based measures of goodness of fit: Akaike Information Criteria (AIC) and Schwartz Criterion (SC). A range of specification diagnostics follows. When estimating a classical regression model (column one and three), it consists of the Jarque-Bera test against non-normality (T_1), the Breusch-Pagan test against heteroskedasticity (T_2), a Lagrange Multiplier test on remaining spatial error autocorrelation (T_3) and a Lagrange Multiplier test on the spatial autoregressive coefficient (T_4). When estimating a spatial lag model (column two and four), the regression diagnostics reported are the same with the differences that we do not find the statistic T_1 (normality is assumed) and that the test on the spatial autoregressive coefficient (T_4) is a Likelihood Ratio test.[27]

Let us first focus our attention on the analysis of the specification of model (13) (first two columns of Table 3). Looking at the diagnostics in column one (classical regression model), the hypothesis of normality of the errors cannot be rejected (in column one, the T_1 statistic is not significant). This implies that the other misspecification tests (various Lagrange multiplier tests), that depend on the normality assumption, can be safely used. There is clear evidence of heteroskedasticity (T_2 statistic is significant) and also both tests for spatial dependence (T_3 and T_4) are highly significant, indicating a potential serious misspecification. We base our choice between the spatial-lag model and the alternative spatial-error model on the comparison between the T_3 and the T_4 statistics. Both statistics are distributed as a chi-squared with one degree of freedom but the second is much more significant than the first one. We then argue that the spatial error test is picking up the omitted spatial lag and that the proper model specification is a spatial lag model (instead of a spatial error model).

Indeed, if we look at column two (spatial lag model), we can observe that the performance of the spatial model has been improved with respect to the standard regression model (without the spatial lag) and it appears correctly specified. In fact, the T_2 statistic is no longer significant providing evidence

[27]For more details and a technical discussion of model validation in spatial regression models (measures of fit and specification diagnostics), see Anselin (1995).

that there is no ignored heteroskedasticity in the model, T_4 is significant denoting that the spatial lag added to the model is relevant and T_3 is not significant confirming that the spatial dependence has been adequately dealt with by incorporating the spatial lag term. If we compare the values of LIK, AIC and SC for this spatial model with the ones reported in the first column, related to a standard regression model, we can observe an increase in the value of LIK and a decrease in the value of AIC and SIC. This is consistent with an evidence that the fit of the model has been improved, as it is to be expected since the spatial lag coefficient turns out to be highly significant.

If we compare the parameters estimates and associated standard errors in column one and two of Table 2, the gain in precision of the estimated coefficients is apparent.

A similar set of statistical considerations can be repeated for the results reported in column three and four of Table 3. Thus, the econometric models (13) and (14), that is spatial lag models, appear to be appropriate and correctly specified.

Appendix 5: List of NUTS3 administrative areas

1 Barnsley, Doncaster and Rotherham

2 Bedfordshire

3 Berkshire

4 Birmingham

5 Blackburn with Darwen

6 Blackpool

7 Bournemouth and Poole

8 Bradford

9 Brighton and Hove

10 Bristol, City of

11 Buckinghamshire

12 Calderdale, Kirklees and Wakefield

13 Cambridgeshire

14 Cheshire

15 Cornwall and Isles of Scilly

16 Coventry

17 Darlington

18 Derby

19 Devon

20 Dorset

21 Dudley and Sandwell

22 Durham

23 Cumbria

24 Derbyshire

25 East Merseyside

26 East Riding of Yorkshire

27 East Sussex

28 Essex

29 Gloucestershire

30 Greater Manchester North

31 Greater Manchester South

32 Halton and Warrington

33 Hampshire

34 Hartlepool and Stockton-on-Tees

35 Herefordshire, County of

36 Hertfordshire

37 Isle of Wight

38 Kent

39 Kingston upon Hull, City of

40 Lancashire

41 Leeds

42 Leicester

43 Leicestershire and Rutland

44 Lincolnshire

45 Liverpool

46 Luton

47 Medway

48 Milton Keynes

49 Norfolk

50 North and North East Lincolnshire

51 North and North East Somerset, South Gloucestershire

52 Nottinghamshire

53 North Yorkshire

54 Northamptonshire

55 Northumberland

56 Nottingham

57 Telford and Wrekin

58 Oxfordshire

59 Peterborough

60 Plymouth

61 Portsmouth

62 Sefton

63 Sheffield

64 Shropshire

65 Solihull

66 Somerset

67 South Teesside

68 Southampton

69 Southend-on-Sea

70 Staffordshire

71 Stoke-on-Trent

72 Suffolk

73 Sunderland

74 Surrey

75 Swindon

76 Thurrock

77 Torbay

78 Tyneside

79 Walsall and Wolverhampton

80 Warwickshire

81 West Sussex

82 Wiltshire

83 Wirral

84 Worcestershire

85 York

Table 1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min.	Max.
$\overline{s}_{NW}$	85	58.91	29.84	0	1
$\overline{s}_{W}$	85	64.62	20.02	0	1
$\overline{t}_{NW}$ *	85	58.1	43.9	5	150
$\overline{t}_{W}$ *	85	46.9	25.5	5	150
$\overline{c}_{NW}$	85	55.4	28.98	27.66	77.35
$\overline{c}_{W}$	85	75.8	20.35	40.06	89.97
θ	85	0.2	0.18	0.05	1.2
h	85	78.99	43.7	34.6	179.89
h_ow	85	61	20.18	10.1	92.4
d	85	893.98	1409.8	14.8	9950.01
network	85	58.01	7.57	9.2	72.2
whites	85	84.64	8.57	75.99	98.06
a	85	84.04	4.62	72.33	91.01
$skills3+$	85	56.31	16.68	33.33	74.56
$y16-24$	85	7.91	5.1	3.4	17.3
$y25-49$	85	27.22	3.25	20	37.2
$y50-64$	85	49.7	4.98	22.5	69.3
e_123	85	34.5	15.90	15	49
e_67	85	72.2	16.2	43	88
e_89	85	60.5	29.3	25	86
w_123	85	93.88	8.51	79.17	114.50
w_45	85	97.82	7.52	87.57	115.18
w_67	85	97.97	7.57	82.16	119.99
w_89	85	99.61	9.07	83.36	135.52
un_dur	85	40.03	30.01	10.9	69.4

* This time corresponds to a return trip in minutes.

Table 2: Estimation Results

	OLS Whites	ML-SAR Whites	OLS Nonwhites	ML-SAR Nonwhites
$cons$	5.6921^{**}	5.0502^{**}	5.888^{**}	5.317^{**}
	(2.1479)	(1.9361)	(2.588)	(2.2089)
Ps	$-$	1.12^{***}	$-$	1.712^{***}
		(0.2768)		(0.4888)
$1/\bar{t}$	13.644^{**}	15.54^{***}	11.854^{**}	11.242^{**}
	(6.146)	(5.3771)	(5.8975)	(5.328)
$1/\bar{t}^2$	4.539^{**}	5.322^{***}	7.018^{***}	7.001^{***}
	(2.121)	(1.7799)	(2.5154)	(2.4308)
$\bar{c}$	0.061^{***}	0.0511^{***}	0.099^{***}	0.087^{***}
	(0.0205)	(0.016)	(0.0345)	(0.0285)
$skills3+$	-0.0609	-0.0478	-0.1403^{*}	-0.1392^{*}
	(0.9602)	(0.8212)	(0.0719)	(0.0711)
a	0.2669^{**}	0.2698^{**}	0.2518^{**}	0.1502^{**}
	(0.1112)	(0.1069)	(0.1009)	(0.059)
$y16-24$	0.582^{**}	0.5489^{**}	0.8783^{*}	0.8656^{**}
	(0.2862)	(0.2525)	(0.4701)	(0.431)
$y25-49$	0.4521	0.509	-0.7124	0.9233
	(1.2779)	(1.1278)	(1.2054)	(1.172)
$y50-64$	-0.5687^{*}	-0.5788^{**}	-0.428	-0.6031^{**}
	(0.2916)	(0.2293)	(0.2779)	(0.2661)
e_123	0.8409	0.8129	-0.2063	-0.2922
	(0.8003)	(0.7028)	(0.296)	(0.2595)
e_67	-0.0182	-0.0156	0.0117	0.0112
	(0.0145)	(0.0139)	(0.198)	(0.1746)
e_89	0.2322	0.2016	0.0521^{*}	0.0455^{**}
	(0.1447)	(0.1306)	(0.0275)	(0.0216)
$whites$	0.0807	0.0804	-0.0064^{*}	-0.0056^{**}
	(0.0562)	(0.0491)	(0.0033)	(0.0022)
$network$	0.0257	0.0312	-0.0057^{*}	-0.0049^{**}
	(0.0608)	(0.0538)	(0.003)	(0.0021)
h	0.0827^{**}	0.071^{**}	0.0661^{*}	0.0555^{**}
	(0.0331)	(0.0294)	(0.0338)	(0.0212)
θ	0.1301^{**}	0.1322^{***}	0.1296^{**}	0.1301^{**}
	(0.0599)	(0.0485)	(0.0628)	(0.052)

w_123	-0.0054	-0.0052	-0.0132	-0.0117
	(0.0062)	(0.0056)	(0.0401)	(0.0368)
w_45	0.0096	0.009	-0.001	-0.0007
	(0.0069)	(0.0058)	(0.0213)	(0.0185)
w_67	0.0009	0.0006	0.106	0.026
	(0.0052)	(0.0034)	(0.104)	(0.0192)
w_89	0.0007	0.0007	0.0151	0.0029*
	(0.0045)	(0.0039)	(0.0101)	(0.0016)
d	0.0008	0.0007	0.063	0.0075
	(0.0204)	(0.0133)	(0.0743)	(0.0629)
h_ow	0.0827	0.0807	-0.0229	-0.0174
	(0.0807)	(0.0755)	(0.0703)	(0.0638)
un_dur	-0.0141**	-0.0121**	0.0444*	0.0321**
	(0.0053)	(0.0046)	(0.024)	(0.016)

*** significant at 1%

** significant at 5%

* significant at 10%

Table 3: Measures of fit and Hypotheses tests

	OLS (Whites)	ML-SAR (Whites)	OLS (Nonwhites)	ML-SAR (Nonwhites)
LIK	-114.21	-106.6	-103.3	-98.76
AIC	274.42	259.2	252.6	243.52
SC	330.601	315.381	308.781	299.709
T_1	3.226		3.568	
(2)	[0.1993]	–	[0.168]	–
T_2	45.356	26.456	43.026	24.022
(22)	[0.0024]	[0.2326]	[0.0047]	[0.3461]
T_3	6.16	2.16	5.98	2.01
(1)	[0.0131]	[0.1416]	[0.0145]	[0.1563]
T_4	11.25	15.22	8.01	9.08
(1)	[0.0008]	[0.0001]	[0.0046]	[0.0026]

Notes:

- degrees of freedom in parentheses

- p-value in squared brackets

Table 4: Partial decomposition of search rate regressions

	Whites	Nonwhites	Racial gap
Actual search rates	64.62	58.91	5.71
Predicted search rates (car and distance)		61.14	
Racial gap explained by car and distance (%)			39.2
Predicted search rates (car)		60.71	
Racial gap explained by car (%)			31.5
Predicted search rates (distance)		59.35	
Racial gap explained by distance (%)			7.7
Racial gap explained by observables (%)			81.7
Racial gap unexplained (%)			18.3