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Spatial mismatch, transport mode and search decisions in England

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Abstract

We develop a theoretical model in which whites mainly use private vehicles to commute whereas nonwhites use public transportation. We show that, for both whites and nonwhites, 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 nonwhites 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, indeed, living in areas where distance to jobs is higher yields the unemployed to 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 nonwhites. Finally, closing the racial gap in car access and distance to jobs would considerably narrow the difference in search intensities between whites and nonwhites.
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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 [15]. 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 US 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 [10], Kain [16], and Ihlanfeldt and Sjoquist [14]). 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 in the vicinity of their neighborhood. Zax and Kain [37] have illustrated this issue by studying a 'natural experiment' (the case 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 includes both of these aspects

[1] In US Metropolitan Statistical Areas, the lack of good public transportation is a real problem (see, e.g., Pugh [22]). 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.

[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 [8] for a survey of the theoretical models of the spatial mismatch.

and to test it using English data. Although the data available are not ideal for the purpose at hand, the empirical analysis attempts to provide some evidence about these issues in UK. 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 (longer time distance to jobs) leads to lower search effort. Indeed, if unemployed workers have bad access to jobs, then they will search less than those who have a better access since it takes more time (and is thus more costly) to gather information about jobs. As a consequence, 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 private transport mode and thus can reach jobs at a lower cost and, as a result, can gather more information than nonwhites.

We then test this model using NUTS3 level data in England.[4] Although the use of aggregate data is motivated by the lack of better data at the individual level, the use of inter-area comparisons also avoids questions of neighborhood selection commonly raised in intracity 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 in similar skills categories to the nonemployed. Our empirical strategy is to investigate to what extent jobless search intensity is related to (time) distance to jobs and different transport modes (races), once the influence of other observable and unobservable area-specific characteristics have been controlled for.

We find that, indeed, living in areas where employed workers' average commuting time is higher yields the jobless 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. These results point to an important relationship between job access and search activity.

We then use these estimated values of search intensities (purged of 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. This evidence may indicate both/either that whites and nonwhites reside at different physical distances from jobs and/or that they use different transport mode. Finally, we explore to what extent inter-racial search effort differentials can be explained by white–nonwhite car access and commuting time differences. We show that, closing the racial gap in car access and distance to jobs would considerably narrow the difference in search intensities between whites and nonwhites in England.

[3] For the spatial mismatch, exceptions include Thomas [33] and Fieldhouse [7] for the UK and Dujardin, Selod and Thomas [6] for Belgium. For the transport mode, exception includes Owen and Green [21] for the UK.

[4] 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.

2. Theoretical model

2.1. The model

There are continuums of workers and firms. There are two types of workers: whites and nonwhites ($j = \mathrm{W}, \mathrm{NW}$). The masses 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., $N_\mathrm{W} + N_\mathrm{NW} = 1$. Whites and nonwhites are totally identical except for the fact that they do not use the same transport mode.[5] 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 are more likely to use their cars.[6] To be more precise, using data drawn from the 1995 Nationwide Personal Transportation Survey, Raphael and Stoll [25] 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.[7] Even more striking, they show that respectively 64 and 46 percent of black and Latino households have one or zero cars whereas this number was 36 percent for white households. In Great Britain, using the 1991 Census data, Owen and Green [21] 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 are using public transport to go to work. Furthermore, 73.6 percent of whites use private vehicles 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 focusing on individual decisions. 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. All workers, whites and nonwhites, live in the area. For simplicity, we do not study the optimal workers' location decision in the area and the land rent formation. We just assume that workers (employed or unemployed) live somewhere in the city and that all workers of the same race with the same employment status obtain the same level of utility.

[5] One may argue that other characteristics, such as education or discrimination, may differentiate white and nonwhite workers. Assuming different levels of education or discrimination against nonwhites in the labor market would in fact reinforce our results. Here, we would like to analyze the consequences of different transport modes on the labor-market outcomes of otherwise identical workers. We believe that differences in transport mode is a key feature of white–nonwhite differences (see the facts below).

[6] We do not investigate here why minority households are so much less likely to own a car. The traditional explanations are based on capital constraints, discrimination in the car insurance market and other such barriers. In this paper, we rather take the mode choice as given and analyze its impact on the labor market outcomes. Observe that, in order to match the real-world figures, we could have assumed that only a fraction of nonwhites uses public transportation and a fraction of whites uses cars. It should be clear that none of our theoretical results would be modified as long as the fraction of nonwhites using public transportation is higher than that of whites and the fraction of whites using cars is higher than that of nonwhites.

[7] 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 12 percent households with no vehicles.

Workers can either be employed or unemployed. The budget constraint of an unemployed worker $j = \mathrm{W}, \mathrm{NW}$ 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 individual 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 having 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 $j = \mathrm{NW}, \mathrm{W}$, 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^0 a positive constant, then for the unemployed workers the total cost per return trip of gathering information about jobs in the employment center is given by[8]:

$$\tau_j x_j + \phi^0 t_j. \tag{2}$$

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, $\phi^0 t_j$, 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 these costs in the same units. If it is expressed in terms of physical distance x_j, it is equal to:

$$\left(\tau_j + \frac{\phi^0}{\mu_j}\right)x_j$$

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

$$(\tau_j \mu_j + \phi^0)t_j.$$

In this paper, we will focus on time distance rather than physical distance because of data availability, but also because in our opinion job access is crucially determined by the former

[8] Observe that the transport-mode literature (see, e.g., Sasaki [28]) has mostly focussed on employed workers and thus this total cost has been written as

$$\tau_j x_j + \phi^1 w_j t_j,$$

where w_j is the wage 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.

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.[9] We can now determine the *total* cost of gathering information about jobs at a distance t_j from the employment center. It is given by

$$\left(\tau_j \mu_j + \phi^0\right) t_j e_j, \tag{3}$$

where $0 \leqslant e_j \leqslant 1$ is the search-effort rate provided by worker j. For example, $e_j = 1$ would be searching every day while $e_j = 1/2$ would be searching every other day. 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 from the employment center is equal to:

$$b = z_j + R(\mu_j t_j) + f_j + C(e_j) + \left(\tau_j \mu_j + \phi^0\right) t_j e_j, \tag{4}$$

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, etc. 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 $C(e_j) + (\tau_j \mu_j + \phi^0) t_j e_j$, which encompasses both search costs that are not distance-related and costs that involve commuting to the employment center.

Let us now focus on the employed worker. He/she has the following budget constraint:

$$w = z_j + R(\mu_j t_j) + f_j + \left(\tau_j \mu_j + \phi^1 w\right) t_j, \tag{5}$$

where w is the wage paid to workers and ϕ^1 is a positive constant that is different to ϕ^0. Irrespective of race, we assume that, at the same distance to jobs t_j, the total cost of search activities for the unemployed is lower than the total commuting cost of the employed, that is, for each $j = \mathrm{NW}, \mathrm{W}$,

$$\left(\tau_j \mu_j + \phi^0\right) e_j < \tau_j \mu_j + \phi^1 w. \tag{6}$$

This is a well documented fact. For instance, Layard et al. [18] show that the time spent in job search activities is quite low compared to the commuting time of the employed.

Furthermore, our assumption that whites use cars and nonwhites public transportation implies that[10]:

$$f_{\mathrm{W}} > f_{\mathrm{NW}}, \qquad \mu_{\mathrm{W}} > \mu_{\mathrm{NW}} \quad \text{and} \quad \tau_{\mathrm{W}} \mu_{\mathrm{W}} < \tau_{\mathrm{NW}} \mu_{\mathrm{NW}}, \tag{7}$$

[9] 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.

[10] As stated above, 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 [19] and Sasaki [28].

i.e., cars used by whites have a higher fixed cost but are faster and, at the same time distance $t_{\mathrm{NW}} = t_{\mathrm{W}} = t$, entails smaller variable cost than public transportation.

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, for each type of worker $j = \mathrm{W}, \mathrm{NW}$, 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:

$$M_j \equiv M(\bar{s}_j u, v), \tag{8}$$

where u and v respectively denote the unemployment rate and the vacancy rate in the area, and $\bar{s}_j$ is the average search efficiency for workers of type j in the area. Each individual's search efficiency s_j 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 $s''(e_j) \leqslant 0$.

As usual (Pissarides [23]), $M_j(.)$ 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

$$\frac{s(e_j)}{\bar{s}_j} \frac{M(\bar{s}_j u, v)}{u} = \frac{s(e_j)}{\bar{s}_j} M(\bar{s}_j, \theta), \tag{9}$$

where $\theta = v/u$ is the labor market tightness for workers of type j. By using the properties of the matching function, it is easy to see that

$$\frac{\partial M(\bar{s}_j, \theta)}{\partial \theta} > 0, \tag{10}$$

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^1 the expected discounted lifetime utility of an employed worker j living at a distance $x_j = \mu_j t_j$ from the employment center and $W_j^0(e_j)$, the expected discounted lifetime utility of an unemployed worker j living at a distance $x_j = \mu_j t_j$ from the employment center are respectively given by

$$rW_j^1 = w - R(\mu_j t_j) - f_j - \big(\tau_j \mu_j + \phi^1 w\big) t_j - \delta\big(W_j^1 - W_j^0(e_j)\big), \tag{11}$$

$$\begin{aligned} rW_j^0(e_j) = {} & b - R(\mu_j t_j) - f_j - C(e_j) - \big(\tau_j \mu_j + \phi^0\big) t_j e_j \\ & + \frac{s(e_j)}{\bar{s}} M(\bar{s}_j, \theta)\big(W_j^1 - W_j^0(e_j)\big), \end{aligned} \tag{12}$$

where $r \in (0, 1)$ is the discount rate, δ, the job destruction rate. Equation (12) has a standard interpretation. When a worker is unemployed today, he/she obtains an instantaneous (indirect) utility equals to $b - R(\mu_j t_j) - f_j - C(e_j) - (\tau_j \mu_j + \phi^0) t_j e_j$. Then, he/she can get a job with probability $M(\bar{s}_j, \theta) s(e_j)/\bar{s}_j$ and, if so, obtains an increase in utility of $W_j^1 - W_j^0(e_j)$. Equation (11) has a similar interpretation.

By subtracting (11) to (12), we obtain

$$W_j^1 - W_j^0(e_j) = \frac{w - b + C(e_j) - (\tau_j \mu_j + \phi^1 w) t_j + (\tau_j \mu_j + \phi^0) t_j e_j}{r + \delta + M(\bar{s}_j, \theta) s(e_j)/\bar{s}_j}. \tag{13}$$

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 v (and thus $\theta = v/u$, the local labor market tightness), the local land rent and the expected discounted lifetime utilities $W_j^1 - W_j^0(e_j)$. By maximizing (12) with respect to e_j, we obtain for $j = \mathrm{W}, \mathrm{NW}$[11]:

$$\frac{\partial W_j^0}{\partial e_j} = -C'\big(e_j^*\big) - \big(\tau_j \mu_j + \phi^0\big)t_j + s'\big(e_j^*\big)\frac{M(\bar{s}_j, \theta)}{\bar{s}_j}\big(W_j^1 - W_j^0\big(e_j^*\big)\big) = 0, \tag{14}$$

where e_j^* is the unique solution of this maximization problem, $s_j^* \equiv s(e_j^*)$ is the corresponding optimal search efficiency and $W_j^1 - W_j^0(e_j)$ is given by (13).

Let us give the intuition of (14). 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, $-C'(e_j^*) - (\tau_j \mu_j + \phi^0)t_j < 0$, so that the worker consumes less of the composite good (budget constraint). On the other hand, increasing search effort e_j increases the long-run (tomorrow) prospects of employment since it increases the probability to obtain a job $M(\bar{s}_j, \theta)s'(e_j)/\bar{s}_j > 0$ and the surplus $W_j^1 - W_j^0(e_j^*)$ 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 $\bar{e}_j^*$ is equal to the individual search effort, i.e., $\bar{e}_j^* = e_j^*$. The average search efficiency of each type of worker is thus given by $\bar{s}_{\mathrm{W}} = s(e_{\mathrm{W}})$ and $\bar{s}_{\mathrm{NW}} = s(e_{\mathrm{NW}})$.

Let us state our first result.

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

Proof. See Appendix A. □

This result shows that, if unemployed workers have bad access to jobs (they 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 is thus more costly*) *to gather information about jobs.* Indeed, when t_j increases, the instantaneous cost of searching (i.e., gathering information about jobs) increases and the eventual surplus of finding a job $W_j^1 - W_j^0(e_j^*)$ is reduced because, the time spent in search activities being shorter than the commuting time of the employed (see (6)), the difference in commuting costs between the employed and

[11] There is a unique solution e_j^* to this maximization problem. See Lemma 1 in Appendix A.

the unemployed increases. As a result, workers residing further away from jobs have not only a higher cost today of gathering information but also a higher commuting cost tomorrow if they find a job. This proposition thus says that, 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 remote locations reduce search intensity for any worker, i.e., $\bar{s}'_j(t_j) < 0$, $j = \mathrm{W}, \mathrm{NW}$. It is easy to see in Appendix A that this relationship between $\bar{s}_j$ and t_j is in fact *nonlinear*.

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 [30]. 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 [30] 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 [34,35]. 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. There are two main differences between Wasmer and Zenou [34,35] and the present paper. Firstly, Wasmer and Zenou do not distinguish between whites and nonwhites and, secondly, the instantaneous cost of searching for a job is $-C'(e_j^*)$ whereas here it is given by $-C'(e_j^*) - (\tau_j \mu_j + \phi^0)t_j$ (see (14)). The latter implies that, in this paper, we open in some sense the black box of Wasmer and Zenou [34,35] by highlighting the importance of transport mode in acquiring information about jobs.

We believe that these three mechanisms that explain why distance to jobs reduces search intensity (lower housing prices, reduced information about jobs, higher costs of gathering information) are complementary. Empirically, Davies and Huff [5] have shown that workers search more efficiently in a closer area (better integrated labor market) while Seater [29] 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 [2] and Chirinko [3] have also shown that there are diminishing returns to search when people live far away from jobs. Finally, Rogers [27] 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 different races who have exactly the same access to jobs, i.e., the same time distance $t_{\mathrm{NW}} = t_{\mathrm{W}} = t$. 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 A. □

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 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 ($t_{\mathrm{NW}} = t_{\mathrm{W}} = t$), then because whites use a private transport mode, they do have a lower variable commuting cost of (time) distance, i.e., $\tau_{\mathrm{W}}\mu_{\mathrm{W}} < \tau_{\mathrm{NW}}\mu_{\mathrm{NW}}$ (see (7)). As a result, it is less costly for whites to gather information about jobs and thus they search more intensively than nonwhites. To be more precise, when the variable pecuniary cost is higher, then workers have a higher instantaneous cost of gathering information but also, if they find a job, a higher commuting cost and thus a lower surplus. Since they have a lower incentive today and tomorrow of searching for a job, their search activity rate is lower.

In this proposition, by fixing job access, we show that transport mode by itself has a significant impact on search intensities. Empirically, Raphael and Stoll [25] 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 [26] 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. [11] 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.

Before going to the data, it is worth observing that the theoretical model is taking location and commute mode as exogenously determined. So one may wonder whether the lower search intensity associated with being further away or relying on slower commute modes adversely affects utility. Indeed, it may argued that, with a complete analysis of the land market, the distance-rent gradient would adjust to account for this disadvantage of being further away, and that the transit dependent and private auto commuters would sort accordingly. This is not always true since land and housing markets are typically not perfectly competitive since they may be influenced by local land use controls including fiscal and exclusionary zoning, and that minority transit dependent households may be geographically constrained by racial discrimination in housing markets.

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.

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 looking for evidence of 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. Data

Our empirical analysis is based on a panel of NUTS3 level data in England from 1994 until 2000. The main data source is the Labour Force Survey (LFS hereafter). It is a quarterly survey. Unfortunately, questions about the usual residence to work travel time in minutes and the usual method of transport are asked only in the autumn quarter until 1999 and in the spring and autumn quarters starting from 2000. Thus, in our analysis, we use only these quarters. In addition, because of small sample sizes per area for ethnic minority groups that satisfy the requirements of our analysis, we aggregate the autumn quarters in years 1994–1996, 1997–1999 and the spring and autumn quarters in 2000, so to end up with *three waves of the panel*. The re-definition of the ethnic variables carried out by the ONS (Office of National Statistics) in the spring quarter of the LFS in 2001 prevents us from using a longer time span.[12]

Given an area, the key variables under investigation are the (average) search intensity, the (average) access to jobs and the (average) access to a private mode of transportation.

Let us discuss first our empirical proxy for search intensity. 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.[13] Thus,

[12] 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).

[13] At the individual level, there is not any other suitable (continuous) variable.

we are forced to use aggregate data. The LFS provides detailed information about the activity of the individuals in the labor market. For each area, we define the average white (nonwhite) search intensity in an area, $\bar{s}_{\mathrm{W}}$ ($\bar{s}_{\mathrm{NW}}$), as the ratio of nonemployed actively searching for jobs (group 1) and the sum of these individuals (group 1) and nonemployed unavailable for work for no valid reason (that is excluding, e.g., long-term sick, disabled, student, temporarily sick) (group 2). In other words, we attempt to capture the behavior of jobless people in the search process by analyzing the determinants of the ratio of active job seekers to 'potential' job seekers. Indeed, the variables that determine the search intensity of group 1 may be the same as those determining the decision not to search, that is to belong to group 2. As circumstances change, the intensity of search (in the sense used in the model, namely the share of time spent looking for job) might increase, and this will cause some additional persons to be classified as active searchers, so that the constructed measure of search intensity increases. It is worthwhile noting that the LFS is a self-reported survey, and the share of time spent looking for work may affect the importance of job searching activity as perceived by the individuals. So it is reasonable to assume that more time spent looking for work induces more persons to declare themselves as active job seekers.

The main drawback of using our indicator stems from the facts that, besides the lack of job-accessibility, workers may be discouraged for a host of other reasons (e.g., discrimination, skill mismatch, etc.), and variations in group 1 may reflect variations in employment. Indeed, more nonemployed job-seekers can also mean more ILO-definition unemployment if unemployment is at the expense of employment.[14] Similarly, the fraction of searchers among jobless will be low if prospects for finding a job are bad (and many jobless people are discouraged), but also if the labor market is booming and all searchers will find a job quickly. We account for these issues by using a large set of control variables in the empirical model. In particular, we include: the proportion of job seekers using friends and relatives as main method of job search, accounting for possible social networks effects that may be a source of discouragement; the population density, accounting for unobserved agglomeration effects that may affect workers' search effort; the number of long term unemployed over the total number of unemployed (by race), as a proxy for the "quality" of the jobless, thus controlling for a possible unobserved heterogeneity in the labor force and the overall (local) employment levels, capturing employment in-and-out flows.[15]

The other control variables are indicators of education, age, economic activity, employment by occupation, output-per-hour-worked, home ownership and an index of local house prices, the tightness of the local labor market and ethnicity, that account for differences in

[14] According to the International Labour Organisation (ILO), the unemployed are those people aged 15 to 74 who are without work but who are immediately available for and actively seeking work. This definition is the one most widely used in the unemployment statistics.

[15] In order to increase our confidence in the validity of our measure, we also performed a further analysis. If our indicator is only the reflection of employment outcomes (variations in group 1) we should find a negative correlation between our measure and employment in-flows: considering as fixed the number of group 2 people, more employed imply less group 1 people and thus a lower value of our ratio. On the contrary, we find a positive and non statistically significant correlation between the two variables. If any relationship, higher employment in-flows appear to be associated with higher values of our ratio. This suggests that our indicator seems in fact to be capturing variations in group 2 people. If higher employment in-flows indicates better prospects of finding a job, they may induce more "potentially" job seekers to actually search for job, as argued in our theoretical model.

Table 1
Descriptive statistics

Variable	Obs.	Mean	Std. dev.	Min.	Max.
Search intensity nonwhites ($\bar{s}_{\mathrm{NW}}$)	90	48.89	38.86	5.11	74.23
Search intensity whites ($\bar{s}_{\mathrm{W}}$)	90	68.21	36.03	24.3	89.49
Commuting time nonwhites ($\bar{t}_{\mathrm{NW}}$)*	90	60.41	36.62	5	150
Commuting time whites ($\bar{t}_{\mathrm{W}}$)*	90	44.81	28.41	5	150
Car access nonwhites ($\bar{c}_{\mathrm{NW}}$)	90	51.41	31.42	21.41	71.31
Car access whites ($\bar{c}_{\mathrm{W}}$)	90	76.71	20.65	41.66	91.37
Long-term unempl. nonwhites	90	49.78	32.72	16.36	68.12
Long-term unempl. whites	90	33.83	27.36	8.54	48.98
Labor market tightness	90	0.27	0.19	0.05	1.25
House price index	90	80.01	47.69	31.11	181.24
Home ownership	90	60.5	24.82	10.20	92.40
Population density	90	893.84	1450.89	18.89	1155.91
Social networks	90	56.21	9.10	9.20	74.21
White population	90	78.14	12.58	71.99	92.05
Active population	90	88.11	6.67	63.34	91.54
Skilled population	90	59.81	18.02	31.33	77.69
Young population	90	9.21	6.15	3.40	17.60
Middle aged population	90	31.02	3.29	18.75	37.20
Old population	90	45.17	5.48	22.50	70.25
Professional employment	90	40.92	17.39	15.00	50.75
Services employment	90	76.32	16.99	43.00	90.25
Manual employment	90	60.12	30.34	24.25	87.00
Total employment	90	94.01	8.55	79.21	98
Output per hour worked	90	19.78	4.52	13.57	26.18

* This time corresponds to a return trip in minutes.

skill composition, population structure, economic activity,[16] sectoral composition, income and wealth, cost of living, labor market conditions, ethnic composition among NUTS3 areas respectively.[17] Precise definitions of all variables used in the empirical analysis can be found in Appendix B. Table 1 contains the summary statistics of all variables.[18]

Let us now turn to the empirical counterparts of the other key variables in the theoretical model. In the empirical spatial-mismatch literature, the measure of job access is obviously crucial (see in particular the survey by Ihlanfeldt and Sjoquist [14]). In fact, the job-access measure has been constructed at different levels of aggregation of the data: individual level (Ihlanfeldt and Sjoquist [13]), neighborhood level (Raphael [24]) and metropolitan level (Weinberg [36]).

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[16] The correlation between the activity rate (labor force over residing population aged 16–64) and our indicator of search intensity is far from perfect, showing a correlation coefficient of 0.63.

[17] 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, Labour Market Statistics Group) or in the UK Data Archive with the exception of house prices, that are available on line from the HM Land Registry. We acknowledge the original data creators and depositors. They bear no responsibility for the analyses and interpretations presented here.

[18] Some NUTS3 administrative areas have been aggregated due to the lack of data of some of the variables. The precise list of the 90 areas considered in the analysis is available upon request.

Our measure of job access is calculated at a rather aggregate level, NUTS3 area. This avoids 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.*[19] Specifically, we define the average white (nonwhite) commuting time in an area, $\bar{t}_{\mathrm{W}}$ ($\bar{t}_{\mathrm{NW}}$), as the ratio between the total time spent travelling to jobs by the white (nonwhite) employed workers living in the area, and the total number of white (nonwhite) employed workers in the area.[20] In short, our proxy of time distance to jobs for a nonemployed 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 white (nonwhite) access to a private mode of transportation (indicated hereafter as car access) in an area, $\bar{c}_{\mathrm{W}}$ ($\bar{c}_{\mathrm{NW}}$), by the number of white (nonwhite) nonemployed workers owning or using a motor vehicle divided by the total number of white (nonwhite) nonemployed workers. Unfortunately, this information is available for the LFS survey only from 2001. Therefore, we use data from the British Household Panel Survey (BHPS, hereafter), aggregated at the area level, for a corresponding period. The underlying assumptions are that whites and nonwhites do not use on average the same transport mode and that employed and nonemployed whites as well as 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 18.82 and 49.2%, respectively, and the percentage of whites and nonwhites using car or scooters is 58.91 and 25.67%, respectively. On the other hand, the percentage of white and nonwhite nonemployed workers owning or using a motor vehicle is 76.71 and 51.41%, respectively. 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 workers.

Table 2 reports the mean values of the key variables. 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. [4], and Gottlieb and Lentnek [9]) and may be due to the fact that nonwhites are in general further away from jobs than whites and/or use slower transport mode (mainly public transportation). The (average) search intensity of white unemployed is well above the one of nonwhite unemployed. We test for the equality of the mean values between whites and nonwhites. Differences in the means are significant at 1 percent level in all cases.[21]

[19] 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 [13], Ihlanfeldt [12], and Kasarda and Ting [17]).

[20] Because whites and nonwhites may compete for different types of jobs, one may argue that the job-access measure should take into account the skill level. In Section 5, for robustness check, we use an alternative job-access measure that takes into account workers' skills.

[21] These results are largely maintained if we control for income and other characteristics.

Table 2
Search intensity, job access and car access between races

	Whites	Nonwhites
	68.21***	48.89
Search intensity	(36.03)	(38.86)
	90	*90*
	44.80***	60.41
Commuting time	(28.41)	(36.62)
	90	*90*
	76.71***	51.41
Car access	(20.65)	(31.42)
	90	*90*

Notes. We report mean values, standard errors (in parenthesis) and number of observations (in italics) by race.
*** Differences in means are significant at 1 percent level.

4. Empirical results

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 unobservable area-specific effects have been controlled for.

4.1. Pooled estimation

We start by providing some evidence of the importance of job access and car access on search intensity.

Consider the following standard panel data model, where we pool all individuals irrespective of their race[22]:

$$\bar{s}_{it} = \frac{\alpha}{\bar{t}_{it}} + \frac{\gamma}{\bar{t}_{it}^2} + \delta \bar{c}_{it} + \sum_{k=1}^{K} \beta_k x_{it}^k + \eta_i + v_{it}, \quad i = 1, \dots, 90, \; t = 1, 2, 3, \tag{15}$$

where $\bar{s}_{it}$ denotes the (average) search intensity in area i at time t, $\bar{t}_{it}$ is the (average) job access in area i at time t, $\bar{c}_{it}$ is the (average) car access in area i at time t, x_{it}^k (for $k = 1, \dots, K$) is a set of K control variables for area i at time t that includes a constant term, time dummies, and all the variables listed in Section 3; η_i is an area-specific fixed effect, controlling for unobservable regional characteristics (e.g., cross-regional differences in matching functions) and v_{it} is a white noise error term.

[22] The variables constructed on the pool of all the individuals follow the same definitions as the race-specific ones.

Table 3
Panel data regression estimation results (model (15))
Key variables

	OLS fixed effects		
	Pooled	Whites	Nonwhites
1/commuting time	11.2343^{***} (3.2350)	10.213^{**} (5.8153)	15.002^{***} (3.8539)
1/commuting time squared	1.8095^{**} (0.9857)	1.6450^{***} (0.8095)	0.9021^{**} (0.4488)
Car access	0.06325^{**} (0.0319)	0.0575^{**} (0.0245)	0.1990^{**} (0.0854)

Notes. (1) Dependent variable: search intensity; (2) time dummies are included; (3) standard errors in parentheses.
** Coefficients are significant at 5 percent level.
*** Idem., 1 percent.

As can be seen in (15), we use the following commuting time function:

$$f(\bar{t}) = \frac{\alpha}{\bar{t}} + \frac{\gamma}{\bar{t}^2}. \tag{16}$$

This function is in line with the result of our theoretical model since it is *nonlinear* (see Eq. (A.1) in Appendix A). It has also the desirable properties that search intensity goes to zero when commuting time tends to infinity and goes to infinity when commuting time tends to zero.[23] 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 effects, any difference in the shape of the estimated function $f(\bar{t})$ 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).

The second column of Table 3 reports the estimation results of a panel data fixed effect estimator for the target variables coefficients (the complete list of estimation results for all the control variables can be found in Table C.1, column two, in Appendix C). Both job access and car access appear to be significant in shaping search intensity patterns and in the direction predicted by the theory.

Let us now turn to the empirical test of our model. 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 accordance with our theoretical model, we undertake two types of analyses. In the first one, we investigate the impact of job access and mode choice on search intensity for each race separately. In the second one, we analyze the impact of job-access and

[23] Other specifications have also been investigated (e.g., an exponential function). The qualitative results remain unchanged.

mode-choice differences between whites and nonwhites on search intensity differences. In particular, using a partial decomposition analysis (Oaxaca [20]), we evaluate the relative importance of car access and distance to jobs on search intensity differences between races.

4.2. 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 Eq. (15) separately for whites and nonwhites.[24] The only differences in the specification of the model in the two cases are in the definition of the dependent variable ($\bar{s}_{\mathrm{W}}$ and $\bar{s}_{\mathrm{NW}}$, respectively), the measure of job access ($\bar{t}_{\mathrm{W}}$ and $\bar{t}_{\mathrm{NW}}$, respectively), the measure of car access ($\bar{c}_{\mathrm{W}}$ and $\bar{c}_{\mathrm{NW}}$, respectively) and our proxy for quality of the unemployed ($\bar{u}_{\mathrm{W}}$ and $\bar{u}_{\mathrm{NW}}$, respectively). The other control variables related to the local area where job seekers live are common to both races and thus to both specifications.

For sake of clarity, we rewrite Eq. (15) by separating the race-specific variables from the other control variables (that include a constant term), and by separating whites and nonwhites. We obtain respectively

$$\bar{s}_{\mathrm{W}_{it}} = \frac{\alpha}{\bar{t}_{\mathrm{W}_{it}}} + \frac{\gamma}{\bar{t}^2_{\mathrm{W}_{it}}} + \delta\bar{c}_{\mathrm{W}_{it}} + \vartheta\bar{u}_{\mathrm{W}_{it}} + \sum_{k=1}^{K}\beta_k x_{it}^k + \eta_i + v_{it},$$
$$i = 1, \dots, 90,\ t = 1, 2, 3, \tag{17}$$

and

$$\bar{s}_{\mathrm{NW}_{it}} = \frac{\alpha}{\bar{t}_{\mathrm{NW}_{it}}} + \frac{\gamma}{\bar{t}^2_{\mathrm{NW}_{it}}} + \delta\bar{c}_{\mathrm{NW}_{it}} + \vartheta\bar{u}_{\mathrm{NW}_{it}} + \sum_{k=1}^{K}\beta_k x_{it}^k + \eta_i + v_{it},$$
$$i = 1, \dots, 90,\ t = 1, 2, 3. \tag{18}$$

The complete set of estimation results is contained in Table C.1 in Appendix C. A comparison between the estimation results of the pooled model (column 2) and the ones of the models stratified by race (columns 3 and 4, respectively), seems to confirm the existence of ethnic-group differences in the determinants of search intensity. For instance, the impact of the percentage of long-term unemployed, not significant in the pooled model, is significant and with opposite sign in the models for whites and nonwhites (negative and positive respectively). This may suggest that nonwhites tend to search more in areas where employment opportunities are low, whereas whites tend to search in areas where they are high. Furthermore, contrarily to the results for the model for whites, nonwhite search intensity is positively and significantly affected by the percentage of employed workers in manual and elementary occupation, and negatively and significantly by the percentage of whites people living in the area and by our proxy of social networks. These results provide some evidence suggesting that nonwhites may be mainly low skilled workers scarcely integrated in the local social networks schemes.

[24] In fact, the use of cross-equation restrictions is rejected by our data. This is why we always use different equations for whites and nonwhites.

The panel data fixed effects estimation results for our key variables are displayed in the third and fourth columns of Table 3 (for whites and nonwhites respectively).[25] Firstly, having access to a car increases search intensity for both whites and nonwhites (estimate of δ positive and significant at 5 percent level). This finding confirms the key role of transport mode in shaping job seekers search effort decisions.

Secondly, the estimated coefficient α 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 controlling for observable and unobservable area characteristics, 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 nonemployed workers 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.

Thirdly, the estimated coefficient of the (inverse) quadratic term, γ, is also positive and statistically significant for both whites and nonwhites, supporting the nonlinearity of the effect of job-accessibility on search intensity as predicted by the theoretical model (Eq. (A.1), in Appendix A).

The estimated functions of commuting time (16) for whites and nonwhites are statistically different from one another.[26] They are plotted in Fig. 1. The diagram shows the influence of job access ($\bar{t}_{\mathrm{W}}$ and $\bar{t}_{\mathrm{NW}}$ for whites and nonwhites, respectively) on search intensity *purged* of the effects of the other control variables (denoted by $\bar{s}^p_{\mathrm{W}}$ and $\bar{s}^p_{\mathrm{NW}}$ for whites and nonwhites, respectively).

These two curves present the following interesting features. Firstly, for both whites and nonwhites, within each race, the unemployed workers' average search intensity 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 conforms to the spatial mismatch hypothesis: the worse the job access, the lower search activities. Secondly, the contrast between the two curves (theoretical prediction in Proposition 2) shows that 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 possible 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,

[25] The qualitative results on our target variables are robust to alternative sets of control variables.

[26] We stack the white panel data set on top of the nonwhite data set and we re-estimate the model including base effects for all the control variables (including the fixed effects) and a full set of interaction terms between all the control variables and a dummy indicating an observation from the nonwhite data set. A simple F-test on the estimated coefficients of the two interaction terms between the nonwhite dummy and the two time-distance variables indicates that they are significantly different from 0 ($F_{2,49} = 14.68$, $p - value = 0.0000$). This provides a formal test of racial differences between the estimated commuting time functions.

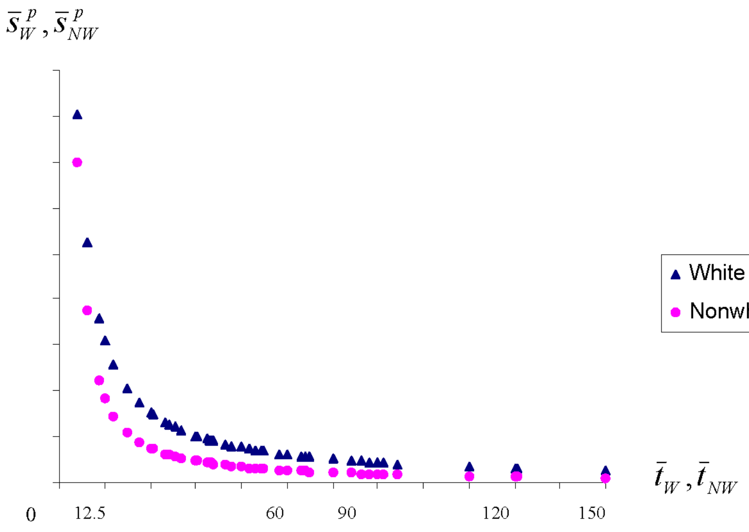

Fig. 1. Relationship between estimated search intensities and job access differences between races.

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 (17) and (18). Clearly, this difference in search intensity is also due to unobservable factors (such as workers' discrimination).

4.3. Inter-race differences

The significant effects of white (nonwhite) average 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 use the familiar Oaxaca technique (Oaxaca [20]) of decomposing any difference in a dependent variable between two groups into the part that is explained by different observable characteristics across groups and the proportion that is due to the same characteristics having a different effect between the two groups. In particular, the difference between white–nonwhite search intensities can be expressed as:

$$\overline{S}^{\mathrm{W}} - \overline{S}^{\mathrm{NW}} = \left(\overline{X}^{\mathrm{W}} - \overline{X}^{\mathrm{NW}}\right)\hat{\beta}^{\mathrm{NW}} + \overline{X}^{\mathrm{W}}\left(\hat{\beta}^{\mathrm{W}} - \hat{\beta}^{\mathrm{NW}}\right), \tag{19}$$

where $\overline{S}^{\mathrm{W}}$ ($\overline{S}^{\mathrm{NW}}$) is the average search intensity of whites (nonwhites), $\overline{X}^{\mathrm{W}}$ ($\overline{X}^{\mathrm{NW}}$) is a row vector of average values for the observable characteristics of whites (nonwhites) and $\hat{\beta}^{\mathrm{W}}$ ($\hat{\beta}^{\mathrm{NW}}$) is the vector of coefficient estimates for whites (nonwhites) from a regression analysis run separately for each group. The first term in the decomposition represents the part of the white–nonwhite search intensity gap that is due to intergroup differences in average values of the observables, and the second term represents the portion of the gap that is "unexplained," i.e., which is due to differences in the estimated coefficients between

Table 4
Decomposition of racial differences in search rates

	Search intensity gap relative to nonwhites	Contribution by group differences in		
Whites		car access and distance to jobs	car access	distance to jobs
	19.32	−9.72	−5.11	−4.61
		Part of gap explained by group differences in		
		car access and distance to jobs	car access	distance to jobs
		50.31%	26.45%	23.86%

Note. The coefficient estimates are those reported in Table 2. See text for more details on calculation of decompositions.

the two groups. We further decompose the first term into the separate contributions from group differences in specific variables, namely car access and (time) distance to jobs.[27]

Specifically, using the estimation results from model (18), we estimate the predicted nonwhite search intensity 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. It reports the contributions from group specific differences in our target variables as well as the corresponding explained portion of the white–nonwhite search intensity in percentage points. As it 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 50.31 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. Inter-race differences in (time) distance to jobs and car access account for almost the same percentage (23.86 and 26.45 respectively) of the disparity between whites' and nonwhites' search intensities.

Finally, for completeness, the overall estimated percentage of racial gap explained by observable variables (population differences in observed characteristics included in the model, first term in Eq. (19)) is 31.4 percent, and the one due to unobservable factors (such as workers' ability and discrimination, second term in Eq. (19)) is 68.6 percent.[28] As it is also apparent in Fig. 1, there is a fair portion of the race gap in search rate left unexplained.

These results, which are quite new for England, have crucial implications for policy makers. They suggest that, for instance, 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 [22]) but rarely emphasized in England.

Our results are in fact quite similar to the ones established in the US. For example, Stoll [31] shows that increasing blacks' and Latinos' access to cars or decreasing their

[27] See, for example, Stoll and Raphael [32] for an application of this technique to measure the contribution of spatial job search quality to racial employment differences in the US.

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

average distance to search areas will lead to greater geographic job search. Raphael and Stoll [25] found that raising minority car-ownership rates to the white car ownership rate would considerably narrow inter-racial employment rate differentials.

5. Robustness checks

In this section, we investigate the robustness of our results to an alternative measure of job access and to an alternative model specification and estimation strategy.

Let us first discuss the motivation underlying the use of an alternative measure of job access. Similarly to other papers on US data, our measure of job access in an area is based on the commuting time of the employed who reside in the area. The implicit assumption when using the employed commuting times to proxy for nonemployed 'commuting' times is that the nonemployed are looking for the same job as the employed who live in their area. Because whites and nonwhites may compete for different kind of jobs, we improve this measure by considering the actual daily two-way travel-to-work time of the employed workers who live nearby who are *in the same skill categories of the nonemployed*. Specifically, we define the average white (nonwhite) commuting time in an area as the ratio between the total time spent travelling to jobs by the employed white (nonwhite) workers living in the area in the same skill categories of nonemployed, and the total number of employed white (nonwhite) workers in the area in the same group. We distinguish between high-skilled and low-skilled jobless and, accordingly, we construct separate measures of search intensity for each race and each skill group. We then run, for each race, two different panel data regressions, one for high-skilled and another for low-skilled. Table 5 shows the panel data fixed effects estimation results for high-skilled whites (second column), high-skilled nonwhites (third column), low-skilled whites (fourth column) and low-skilled

Table 5
Robustness analysis estimation results
Key variables

	OLS fixed effects				ML spatial error model	
	High-skilled whites	High-skilled nonwhites	Low-skilled whites	Low-skilled nonwhites	Whites	Nonwhites
$1/\bar{t}$	5.9213** (2.8153)	8.5442** (3.4685)	12.255*** (4.3414)	18.341*** (5.788)	13.461*** (4.2821)	15.772*** (3.594)
$1/\bar{t}^2$	0.6945** (0.3285)	0.0321** (0.0182)	1.8095** (0.8568)	1.002** (0.5661)	1.6890*** (0.5576)	5.981*** (2.0107)
$\bar{c}$	0.0257** (0.0121)	0.1012** (0.0512)	0.08613*** (0.028674)	0.1843*** (0.0756)	0.0770*** (0.0241)	0.1612*** (0.0354)
λ	–	–	–	–	0.866*** (0.3744)	1.211*** (0.5203)

Notes. (1) Dependent variable: search intensity; (2) $\bar{t}$: commuting time, $\bar{c}$: car access; (3) time dummies are included in panel regressions; (4) standard errors in parentheses.

** Coefficients are significant at 5 percent level.

*** Idem., 1 percent.

nonwhites (fifth column). The estimated coefficients of job access and car access remain significant and with the expected sign in all cases, although reduced in magnitude with respect to the corresponding race-specific results (Table 3). Thus, the main results of our analysis appear to be robust with respect to the measure of job access. Incidentally, note that we find that the estimated impact of both car access and job access on search intensity is larger for low skilled workers, particularly nonwhites. This may be consistent with the fact that low-skilled jobless are discouraged in looking for jobs if they live in areas where employment is too distant, because the wage cannot compensate for the commute if they do obtain a job. Also, if low-skilled jobs are advertised locally and if low-skilled workers reside far away from the business center, their search is discouraged by high search cost. This may be particularly true for nonwhites who, according to the spatial mismatch hypothesis, reside far away from the business center.

For robustness check, we have also used other characterizations of the commuting time distribution. Indeed, if for example, jobs close to home are preferred to jobs far away, the employed may have already filled nearby opportunities, and thus the average commuting time might underestimate how far the marginal nonemployed workers would have to travel to gather information and to work. The qualitative results are roughly the same if we use either the median point or the 75th percentile of the commuting time distribution instead of the average commuting time.

We now turn to analyze an alternative specification of model (15). When the units under investigation have a geographical connotation, spatially correlated unobservable variables may produce spatial correlation in the errors of equations describing the relationships among economic variables. In order to assess correctly the significance of the coefficients of the variables of interest, this possible spatial correlation cannot be neglected. In many cases, exploiting the longitudinal structure of a data set offers a valid device to account for these effects. In other cases, a spatial modeling framework be more appropriate. We investigate the relevance of this issue in our case by estimating a regression model with a spatial autoregressive process for the error term. Instead of using a panel data fixed effect model that controls for spatial components by differencing out unobservable factors across areas, we constraint the random effects to be spatially correlated. Indeed, both the theoretical model and its empirical equivalent may miss some determinants of search activity, and if these determinants are correlated across areas, then the spatial error model is appropriate. For example, maybe (unobserved) road congestion deters search, with congestion being high in highly urbanized areas, which may be spatially adjacent, and low in less-urbanized areas, which are also spatially adjacent.[29] In other words, we test the robustness of our result with respect to different assumptions on unobservable factors. As a result, we estimate model (15) on the variables averaged over time. The model specification is as follows[30]:

$$\bar{s} = \frac{\alpha}{\bar{t}} + \frac{\gamma}{\bar{t}^2} + \delta\bar{c} + \vartheta\bar{u} + X\beta + \varepsilon,$$
$$\varepsilon = \lambda P\varepsilon + \xi,$$

[29] We are grateful to Jan Brueckner for providing this example.

[30] Theoretical details on the spatial error model can be found, among others, in Anselin [1].

where $\bar{s}$, $\bar{t}$, $\bar{c}$ and $\bar{u}$ are $N \times 1$ vectors of observations ($N = 90$, the number of areas considered) on the race-specific variables, X is a $N \times k$ matrix of observations on the control variables (including a constant term), ε is a $N \times 1$ vector of normally distributed error terms, $P\varepsilon$ is a $N \times 1$ vector of spatial lags for the errors, that 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), λ is the spatial autoregressive coefficient and ξ is a $N \times 1$ vector of normally distributed random error terms, with means 0 and constant variances σ^2.[31]

The Maximum Likelihood estimation results (ML) for our key variables are contained in the last two columns of Table 5 (for whites and nonwhites respectively).[32] The estimate of the spatial autoregressive parameter, λ (in the last row of each column), highly significant in both columns, points to the importance of residual spatial autocorrelation. However, the estimation results on the target variables are qualitatively unchanged, proving the robustness of the panel data estimation results discussed above (Table 3).[33]

6. Conclusion

This paper has shed some light on the link between job access, transport mode and search activity rates. 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 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 attempted to test 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 yields the nonemployed 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, nonemployed whites search more intensively than nonemployed nonwhites. Our final re-

[31] 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.

[32] For details on the adaptation of the Maximum Likelihood estimator to this spatial case and on the estimation procedure see, among others, Anselin [1].

[33] The complete list of estimation results for all the control variables both for the two spatial error models stratified by race and for the four panel regressions by race and skill categories are available upon request.

sults provide evidence that differences in search activities between whites and nonwhites are due to differences in job access as well as differences in car ownership.

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Appendix A. Proofs related to the theoretical model

Proof of Proposition 1. Before proving this proposition, let us state the following lemma.

Lemma 1. *There is a unique solution e_j^* to the first order condition* (14).

Proof. By differentiating (14) with respect to e_j^* and by observing that $\bar{s}_j = s(e_j)$ and $M(\bar{s}_j, \theta)/\bar{s}_j = M(1, \theta/\bar{s}_j)$, we obtain the following second order condition (*SOC* hereafter):

$$\begin{aligned} SOC \equiv & -C''(e_j) + s''(e_j)\frac{M(\bar{s}_j,\theta)}{\bar{s}_j}\big(W_j^1 - W_j^0\big(e_j^*\big)\big) \\ & + s'(e_j)\frac{M(\bar{s}_j,\theta)}{\bar{s}_j}\frac{\partial(W_j^1 - W_j^0(e_j^*))}{\partial e_j} \\ & - \big[s'\big(e_j^*\big)\big]^2\big(W_j^1 - W_j^0(e_j)\big)M_2\theta/\bar{s}_j^2, \end{aligned}$$

where $M_2 > 0$ is the derivative of $M(\cdot)$ with respect to its second argument. *SOC* is always negative because, using (13) and (14), it is easy to see that $\partial(W_j^1 - W_j^0(e_j^*))/\partial e_j = 0$, and thus we have:

$$\begin{aligned} SOC \equiv & -C''(e_j) + s''(e_j)\frac{M(\bar{s}_j,\theta)}{\bar{s}_j}\big(W_j^1 - W_j^0\big(e_j^*\big)\big) \\ & - \big[s'\big(e_j^*\big)\big]^2\big(W_j^1 - W_j^0(e_j)\big)M_2\theta/\bar{s}_j^2 < 0. \qquad \square \end{aligned}$$

Let us now prove Proposition 1. By totally differentiating (14), we obtain

$$\frac{\partial e_j^*}{\partial t_j} = -\frac{-(\tau_j\mu_j + \phi^0) + s'(e_j)\frac{M(\bar{s}_j,\theta)}{\bar{s}_j}\frac{\partial(W_j^1 - W_j^0(e_j^*))}{\partial t_j}}{SOC}. \tag{A.1}$$

Observe that, by differentiating (13), we obtain

$$\frac{\partial(W_j^1 - W_j^0(e_j^*))}{\partial t_j} = \frac{-(\tau_j\mu_j + \phi^1 w) + (\tau_j\mu_j + \phi^0)e_j}{r + \delta + M(\bar{s}_j,\theta)} < 0,$$

since the time spent in job-search activities is always shorter than the commuting time of the employed (see (6)). As a result, the numerator of $\partial e_j^*/\partial t_j$ in (A.1) is negative and, since $SOC < 0$, we have

$$\frac{\partial e_j^*}{\partial t_j} < 0.$$

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

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

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

$$\frac{\partial \bar{e}_j^*}{\partial t_j} < 0 \quad \text{and} \quad \frac{\partial \bar{s}_j^*}{\partial t_j} < 0. \qquad \square$$

Proof of Proposition 2. We want to compare a white and a nonwhite unemployed worker located at exactly the same time distance, i.e., $t_{\mathrm{NW}} = t_{\mathrm{W}} = t$. It is easy to see from (14) that the main difference between these two workers is the variable pecuniary cost. But since by (7), $\tau_{\mathrm{W}}\mu_{\mathrm{W}} < \tau_{\mathrm{NW}}\mu_{\mathrm{NW}}$, then obviously the optimal effort level of nonwhites will be lower than that of whites, i.e., $e_{\mathrm{NW}}^* < e_{\mathrm{W}}^*$.

To see that more formally, we can totally differentiating (14). We obtain

$$\frac{\partial e_j^*}{\partial(\tau_j\mu_j)} = -\frac{-t + s'(e_j^*)\frac{M(\bar{s}_j,\theta)}{\bar{s}_j}\frac{\partial(W_j^1 - W_j^0(e_j^*))}{\partial(\tau_j\mu_j)}}{SOC}.$$

Since by Lemma 1, $SOC < 0$, we need to show that

$$-t + s'(e_j^*)\frac{M(\bar{s}_j,\theta)}{\bar{s}_j}\frac{\partial(W_j^1 - W_j^0(e_j^*))}{\partial(\tau_j\mu_j)} < 0.$$

By differentiating (13), we have

$$\frac{\partial(W_j^1 - W_j^0(e_j^*))}{\partial(\tau_j\mu_j)} = \frac{-(1-e_j)t}{r + \delta + M(\bar{s}_j,\theta)} < 0,$$

which implies that

$$\frac{\partial e_j^*}{\partial(\tau_j\mu_j)} < 0.$$

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 $\bar{e}_{\mathrm{W}}^* > \bar{e}_{\mathrm{NW}}^*$ and $\bar{s}_{\mathrm{W}}^* > \bar{s}_{\mathrm{NW}}^*$. $\square$

Appendix B. Description of variables

Search intensity ($\bar{s}_{\mathrm{W}}(\bar{s}_{\mathrm{NW}})$): ratio between white (nonwhite) jobless actively searching for a job and the sum of white (nonwhite) jobless actively searching for a job and white (nonwhite) jobless not searching for a job and/or unavailable to work, without a valid reason. Source: LFS-INECA variable (derived variable).

Commuting time ($\bar{t}_{\mathrm{W}}(\bar{t}_{\mathrm{NW}})$): ratio between total time spent travelling to jobs by white (nonwhite) employed workers, and total number of white (nonwhite) employed. Source: LFS.

Car access ($\bar{c}_{\mathrm{W}}(\bar{c}_{\mathrm{NW}})$): ratio between white (nonwhite) nonemployed owning or using a motor vehicle, and total number of white (nonwhite) nonemployed. Source: BHPS.

Long-term unemployment ($\bar{u}_{\mathrm{W}}(\bar{u}_{\mathrm{NW}})$): ratio between white (nonwhite) workers who have been unemployed for more than one year and the total number of white (nonwhite) unemployed. Source: LFS.

Active population: ratio between population of working age economically active and population of working age (16–64). Source: LFS (available from NOMIS).

Skilled population: ratio between economically active population above NVQ2 (NVQ3, NVQ4 and higher)[34] and with other qualifications and population of working age economically active. Source: LFS (available from NOMIS).

Young population: population aged 16–24 over population aged more than 16. Source: LFS (available from NOMIS).

Middle-aged population: population aged 25–49 over population aged more than 16. Source: LFS (available from NOMIS).

Old population: population aged 50 up to retirement age over population aged more than 16. Source: LFS (available from NOMIS).

Professional employment: all in employment working as managers, professional and technical occupations (*SOC* $1, 2, 3$)[35] over total number of employed. Source: LFS (available from NOMIS).

Services employment: 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).

Manual employment: 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).

Total employment: employed over labor force. Source: LFS (available from NOMIS).

White population: white population aged more than 16 over total population aged more than 16. Source: LFS (available from NOMIS).

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

[34] The NVQs are levels of vocational qualifications based on statements of performance standards which describe what competent people in a particular occupation are expected to be able to do. They are organised into five levels. For precise definitions see http://www.dfes.gov.uk/nvq/.

[35] The Standard Occupational Classification (SOC) system, developed by the US Department of Labor classifies workers into occupational categories. Each broad occupation includes detailed occupations requiring similar job duties, skills, education, or experience (further details in http://www.bls.gov/soc/home.htm). We use the classification into 9 major groups adopted by our data-source NOMIS.

Labor market tightness: ratio between unfilled vacancies and unemployed in the local area. Source: NOMIS.

Home ownership: persons home owners over population aged more than 16. Source: LFS.

House price index: index (fixed weight) of house prices in the local area. The weights are the share of each type of houses sales in total UK sales of houses. Source: HM Land Registry.

Output per hour worked: estimates of workplace-based gross value added at basic prices per hour worked. Total hours worked by employees computed from data on the numbers of full-time employees and of part-time employees and the average weekly hours worked by each group. Source: ONS Annual Business Inquiry.

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

Appendix C. Complete list of estimation results of Table 3

Table C.1
Panel data regression estimation results (model (15))
Complete list of variables

	OLS fixed effects		
	Pooled	Whites	Nonwhites
Constant	4.7412*** (1.1908)	4.3102*** (1.7427)	7.9109*** (1.3483)
1/commuting time	11.2343*** (3.2349)	10.213** (5.8153)	15.002*** (3.8539)
1/commuting time squared	1.8095** (0.9857)	1.6450*** (0.8095)	0.9021** (0.4488)
Car access	0.06325** (0.0318)	0.0575** (0.0245)	0.1990** (0.0854)
Long-term unemployment	−0.089 (0.0768)	−0.08091** (0.0344)	0.0161** (0.0074)
Skilled population	−0.0595 (0.0647)	−0.0541 (0.8516)	−0.1867 (0.7580)
Active population	0.5764*** (0.12906)	0.5239*** (0.1208)	0.2389** (0.1019)
Young population	0.5742** (0.3118)	0.5220** (0.2274)	0.7992** (0.2130)
Middle aged population	0.4465 (1.0535)	0.4059 (1v1276)	−0.6310 (1.1049)
Old population	−0.5642*** (0.16938)	−0.5129** (0.2745)	−0.3612* (0.2269)
Professional employment	0.6614* (0.4571)	0.6013 (0.7475)	−0.1828 (0.7472)

(*continued on next page*)

Table C.1 (*continued*)
Complete list of variables

	OLS fixed effects		
	Pooled	Whites	Nonwhites
Services employment	0.0064 (0.1616)	−0.0240 (0.0169)	0.0113 (0.0165)
Manual employment	0.06789 (0.0571)	0.0799 (0.0985)	0.0503* (0.0267)
White population	0.051378 (0.0422)	0.07398 (0.0577)	−0.0044* (0.0029)
Social networks	0.00921483 (0.0077)	0.01953 (0.0454)	−0.00297* (0.0021)
Labour market tightness	0.0712*** (0.0275)	0.0829** (0.0462)	0.1114*** (0.0387)
Output per hour worked	0.1980*** (0.0267)	0.1800*** (0.0431)	0.3572*** (0.0651)
Total employment	−0.6852*** (0.1738)	−0.6229*** (0.2319)	−0.162** (0.0921)
Population density	0.0263** (0.0143)	0.0367** (0.0194)	0.0634*** (0.0192)
Home ownership	0.0653** (0.0371)	0.0594 (0.0699)	−0.02746 (0.0679)
House price index	0.0794*** (0.0274)	0.0722*** (0.0280)	0.0735*** (0.0371)

Notes. (1) Dependent variable: search intensity; (2) time dummies are included; (3) standard errors in parentheses.
* Coefficients are significant at 10 percent level.
** Idem., 5 percent.
*** Idem., 1 percent.

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