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Search Activities, Cost of Living and Local Labor Markets

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Abstract

A model is considered in which optimal search intensity is a result of a trade off between short run losses due to higher search costs (more interviews, commuting...) and long-run gains due to a higher chance of finding a job. We show that this optimal search intensity is higher in areas characterized by larger cost of living and/or higher labor market tightness. This model is then tested for England on sub-regional data. We estimate a spatial error model and we find that both the local cost of living and the local labor market tightness are found to have a positive and significant effect on unemployed average search intensity. These findings are consistent with the prediction of the theoretical model.

Key words: job matching, search intensities, spatial correlation.

JEL Classification: C21, J64, R1.

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1 Introduction

There seems to be a growing awareness that some patterns of economic variables might be due to spatial rather than purely economic factors. This is particularly true in the labor market (see, for example, Topa, 2001 and Manning, 2003) and more especially for job search activities since a spatial dispersion of agents creates more frictions and thus more unemployment.

The aim of this paper is to investigate, both theoretically and empirically, the relationship between job search and space by focusing on the impact of local cost of living and local labor market tightness on search activities. We believe that the understanding of these relationships is crucial for regional policies.

From a theoretical point of view, few models have introduced a spatial analysis in a search-matching model. Exceptions include Seater (1979), McCormick and Sheppard (1992), Rouwendal (1998), Ortega (2000), Coulson, Laing and Wang (2001), Sato (2001), Wasmer and Zenou (2002), Smith and Zenou (2003). Contrary to these models, our focus is on search intensity and its relationship with cost of living and labor market tightness in a local labor market.

From an empirical point of view, few papers have tested spatial search models. Most of the related empirical literature focuses on the aggregation of the matching function across space and on the interaction between local matching and regional migration or commuting behavior (see in particular the survey by Petrongolo and Pissarides, 2001, and also Jackman and Savouri, 1992, Burda and Profit, 1996, Burgess and Profit, 2001). In the present paper, we analyze a different issue, namely the relationship between the local average job-search intensity, on the one hand, and the local cost of living and/or the local labor market tightness, on the other.

To be more precise, we first develop a simple model in which optimal search intensity is a result of a trade off between short run losses due to higher cost of search effort (more interviews, commuting...) and long-run gains due to higher chance to find a job. We show that this optimal search intensity is higher in areas characterized by larger cost of living and/or higher labor market tightness. The intuition is as follows. When the cost of living increases, workers consume less and thus have more leisure both when they are employed and unemployed. However, because the employed are assumed to value more leisure than the unemployed, the difference in intertemporal utility between the employed and the unemployed increases, and as a result, the unemployed workers search more

actively because the reward of a successful match is higher. Similarly, when the labor market tightness rises, it becomes easier to find a job (there are relatively more jobs available compared to the unemployed) and thus the returns to search are higher. As a result, workers put more effort in search activities.

Empirical support for this predictions is found in a British panel of sub-regional data for the year 2000. A spatial lag model is estimated. Once spatial effects and the influence of different area-specific characteristics have been controlled for, both the cost of living and the labor market tightness are found to have a positive and significant effect on the unemployed search intensity.

The remainder of the paper is organized as follows. Section 2 presents the theoretical model and its main predictions. Section 3 describes the data, the empirical models and the estimation results. Finally, Section 4 concludes.

2 Theoretical model

We develop a simple model that explains how search effort decisions are made and how cost of living and labor market tightness influence this choice.

Let us first explain the macroeconomic environment. Time is continuous and workers live forever. All workers are ex ante identical. 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:

$$M \equiv M(\bar{s}U, V) \tag{1}$$

where U and V respectively denote the number of unemployed workers and vacancies. Each unemployed worker $k = 1, \dots, U$ has a search intensity equal to s_k . Accordingly, \bar{s} represents the average intensity of search of the U unemployed workers. As usual (Pissarides, 2000), $M(\cdot)$ 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 for an unemployed worker k with search intensity s_k is given by:

$$p(s_k, \bar{s}, \theta) \equiv \frac{s_k}{\bar{s}U} M(\bar{s}U, V) = \frac{s_k}{\bar{s}} M(\bar{s}, \theta) \tag{2}$$

where $\theta = V/U$ is the labor market tightness. By using the properties of the matching function, it is easy to see that

$$\frac{\partial p(s_k, \bar{s}, \theta)}{\partial \theta} > 0 \tag{3}$$

since more vacancies in the area increase the probability to find a job whereas more unemployed workers decreases this probability.

Similarly, the probability to fill a vacancy is

$$q(\bar{s}, \theta) \equiv \frac{M(\bar{s}U, V)}{V} = M\left(\frac{\bar{s}}{\theta}, 1\right)$$

with

$$\frac{\partial q(\theta)}{\partial \theta} < 0 \tag{4}$$

Equations (3) and (4) express the search externalities that are present in this model. The higher the unemployed who are searching for a job, the easier is to fill a vacancy but the more difficult is to find a job. Similarly, the higher the vacant firms that are searching for a worker, the easier is to find a job but the more difficult is to fill a vacancy.

We now focus on the behavior of an unemployed worker that searches for a job and analyze how this behavior is affected by factors related to his/her residential location, such as living costs and the tightness of the local labor market.

Let us first determine the instantaneous utility function. Let us denote by the superscript ‘0’ the *unemployed* group and by the superscript ‘1’ the *employed* group. Workers have the following Cobb-Douglas preferences representable by:

$$V(l^j, z^j) = \alpha^j \log l^j + (1 - \alpha^j) \log z^j \quad j = 0, 1 \tag{5}$$

where $0 < \alpha^j < 1$, and l^j and z^j are respectively leisure and composite good consumptions for workers of type $j = 0, 1$. We assume that $\alpha^1 > \alpha^0$, which means that, for the same amount of leisure, employed workers value more leisure than unemployed workers or equivalently they value less the composite good consumption ($1 - \alpha^1 < 1 - \alpha^0$). This is because working is a more stressful activity than searching and leisure is a scarcer ‘resource’ for those who are employed. As a result, leisure for the employed (i.e. time spent non working) is more valued than leisure for the unemployed (i.e. time spent non searching). The budget constraint of an employed worker is given by

$$wT = h z^1 \tag{6}$$

where w is the per-hour wage, h is the price of the composite good or equivalently the *cost of living* and T denotes the amount of working hours. T is assumed to be the same and constant across workers, an assumption that

agrees with most jobs in the vast majority of developed countries. Each worker provides a fixed amount of labor time T . Thus, the time constraint of an employed worker can be written as:

$$1 - T = l^1 \quad (7)$$

in which the total amount of time is normalized to 1 without loss of generality. Observe that, since total time is one, l^1 is the fraction of time spent in leisure.

By plugging (6) and (7) in (5), we obtain the following indirect utility for the employed workers:

$$V^1 \equiv V(w, h) = \alpha^1 \log(1 - T) + (1 - \alpha^1) \log\left(\frac{wT}{h}\right) \quad (8)$$

Concerning the unemployed, the utility is given by (5). For an unemployed worker with search intensity s_k , the budget constraint can be written as

$$b - C(s_k) = h z_k^0 \quad (9)$$

where b is the unemployment benefit and $C(s_k)$ is the total cost of searching for jobs. The latter encompasses the costs of buying newspapers, commuting, contacting friends, phone calls, interviews... We assume that

$$C'(s_k) > 0 \quad , \quad C''(s_k) > 0 \quad (10)$$

i.e. more search effort implies more search costs and it is even more costly at the margin (convex function). The time constraint is equal to:

$$l_k^0 + s_k = 1 \quad (11)$$

In this formulation, the leisure time for unemployed workers is taken to include all time spent not searching for work. Thus, the expected fraction of leisure time for an unemployed worker with search intensity, s_k , is simply $1 - s_k$.

By plugging (9) and (11) in (5), we obtain the following indirect utility function for the unemployed with search intensity s_k :

$$V^0 \equiv V(b, h, s_k) = \alpha^0 \log(1 - s_k) + (1 - \alpha^0) \log\left(\frac{b - C(s_k)}{h}\right) \quad (12)$$

We are now equipped to write W_k^0 , the expected discounted lifetime utility of an unemployed worker with search intensity s_k and W^1 , the expected discounted lifetime utility of an employed worker (Bellman equation). In steady-state, they are given by:

$$\begin{aligned} rW_k^0 &= V^0 + \frac{s_k}{\bar{s}} M(\bar{s}, \theta) (W^1 - W_k^0) \\ &= \alpha^0 \log(1 - s_k) + (1 - \alpha^0) \log\left(\frac{b - C(s_k)}{h}\right) + \frac{s_k}{\bar{s}} M(\bar{s}, \theta) (W^1 - W_k^0) \end{aligned} \quad (13)$$

$$\begin{aligned}
rW^1 &= V^1 - \delta (W^1 - W_k^0) \\
&= \alpha^1 \log(1 - T) + (1 - \alpha^1) \log\left(\frac{wT}{h}\right) - \delta (W^1 - W_k^0)
\end{aligned} \tag{14}$$

where $r \in (0, 1)$ is the discount rate and δ is the job destruction rate. Equation (13) has a standard interpretation. When a worker is unemployed today, he/she obtains an instantaneous (indirect) utility equals to V^0 . Then, he/she can get a job with a probability $\frac{s_k}{\bar{s}} M(\bar{s}, \theta)$ and, if so, obtains an increase in utility of $W^1 - W_k^0$. Equation (14) has a similar interpretation.

By subtracting (14) to (13), we obtain:

$$W^1 - W_k^0 = \frac{V^1 - V^0}{r + \delta + M(\bar{s}, \theta) s_k / \bar{s}} \tag{15}$$

Let us now study the search effort decision. When making this decision, the unemployed takes as given the total unemployment level U , the total number of vacancies V (and thus $\theta = V/U$ the labor market tightness), the cost of living h and the expected discounted lifetime utilities W_k^0 and W^1 .

By maximizing (13) with respect to s_k , we obtain¹

$$\begin{aligned}
\frac{\partial W_k^0}{\partial s_k} &= \frac{\partial V^0}{\partial s_k^*} + \frac{M(\bar{s}, \theta)}{\bar{s}} (W_k^1 - W_k^0) = 0 \\
\Leftrightarrow \frac{M(\bar{s}, \theta)}{\bar{s}} (W_k^1 - W_k^0) &= \alpha^0 \frac{1}{1 - s_k^*} + (1 - \alpha^0) \frac{C'(s_k^*)}{b - C(s_k^*)}
\end{aligned} \tag{16}$$

and where s_k^* is the unique solution of this maximization problem.

Let us give the intuition of (16). When choosing s_k^* , there is a fundamental trade-off between short-run and long-run benefits for an unemployed worker. On the one hand, increasing search effort s_k is costly in the short run (more phone calls, more interviews, less leisure) as it decreases instantaneous utility ($\partial V^0 / \partial s_k < 0$), but, on the other, it increases the long-run prospects of employment ($M(\bar{s}, \theta) (W_k^1 - W_k^0) / \bar{s}$ is the marginal return of employment).

At the symmetric equilibrium, all workers provide the same search intensity so that $s_k^* = s^* = \bar{s}^*$. Thus, using (15), equation (16) can be written as

$$\alpha^0 \frac{1}{1 - \bar{s}^*} + (1 - \alpha^0) \frac{C'(\bar{s}^*)}{b - C(\bar{s}^*)} = \frac{M(\bar{s}^*, \theta)}{\bar{s}^*} \frac{V^1 - V^0}{r + \delta + M(\bar{s}^*, \theta)} \tag{17}$$

¹See Lemma 1 in Appendix 1 that shows that there is a unique solution to this maximization problem.

We assume that wages w , the number of job created V , the unemployment level U , and thus θ are given.² Our main result is as follows:

Proposition 1

- (i) *The higher the cost of living h , the higher the average search intensity $\bar{s}^* = s_k^*$ of the unemployed workers.*
- (ii) *The higher the labor market tightness θ , i.e. the higher the number of vacancies V or the lower the unemployment level U , the higher the average search intensity $\bar{s}^* = s_k^*$ of the unemployed workers.*

Proof. See Appendix 1.

As stated above, when deciding the optimal level of search effort, each unemployed worker trades off the short run losses of increasing effort (higher cost of search effort $C(s_k)$ and less leisure time and thus lower instantaneous utility V^0) with the long-run gains (higher chance to get a job and to enjoy an intertemporal utility difference between employment and unemployment). Proposition 1 analyzes the effect of living costs h (short-run effect) and the one of the labor market tightness θ (long-run effect) on search effort s_k^* and average search intensity \bar{s}^* .

When costs of living h increase, workers reduce their composite consumption both when they are employed and unemployed. However, because the employed value more leisure ($\alpha^1 > \alpha^0$) and thus less composite good consumption ($1 - \alpha^1 < 1 - \alpha^0$) than the unemployed, the difference in instantaneous utility $V^1 - V^0$ increases since the unemployed are more affected by this increase in h than the employed. Now, because, the marginal intertemporal utility difference between employment and unemployment ($W^1 - W_k^0$) is equal to the marginal instantaneous utility difference between employment and unemployment ($V^1 - V_k^0$), i.e.

$$\frac{\partial (W^1 - W_k^0)}{\partial h} = \frac{\partial (V^1 - V_k^0)}{\partial h}$$

²In fact, to endogenize these variables and to close the model is quite easy since it suffices to add a free entry condition for θ , a wage bargaining determination for w and a steady-state flows in and flows out equation for U . This is now standard (Pissarides, 2000). However, the aim of the theory is to shed some light on the relationship between local average search activity and local characteristics by providing a mechanism for the link between \bar{s}^* and h and between \bar{s}^* and θ , for a given wage and a given unemployment level, that can be easily tested. In the empirical analysis, wages are used as control variables.

an increase in costs of living h raises $W^1 - W_k^0$ and, as a result, unemployed workers search more actively because of better returns to search.

Similarly, when the labor market tightness θ rises, it becomes easier to find a job (there are relatively more jobs available compared to the unemployed) and thus the returns to search are higher. As a result, workers put more effort in search activities.

More generally, the basic message of this model is as follows. If we compare two areas (counties, cities, regions), then, controlling for wages and workers' characteristics, the unemployed workers living either in the more expensive area and/or in the area with the higher labor market tightness, search more on average.

3 Empirical Analysis

The aim of this empirical investigation is to test the results of Proposition 1, namely the positive relationships between \bar{s}^* and h and between \bar{s}^* and θ . Figure 1 shows three quantile maps that depicts the geographical distribution of the search rate (first panel), the tightness of the local labor markets (panel on the left) and our proxy for costs of living, i.e. house prices, (panel on the right) in England at the NUTS3 level of spatial disaggregation for the year 2000. It appears evident that most of the areas with high (low) levels of local search rate are the areas with high (low) levels of local labor market and cost of living.

Our empirical strategy is to estimate the impact of the local cost of living and the local labor market tightness on the average search intensity, once the influence of other area specific characteristics (skill composition, population structure, economic activity, sectorial composition, quality of the unemployed, income and wealth, ethnic composition, (time) distance to jobs, motor vehicle usage, agglomeration effects, social networks) and spatial effects have been controlled for.

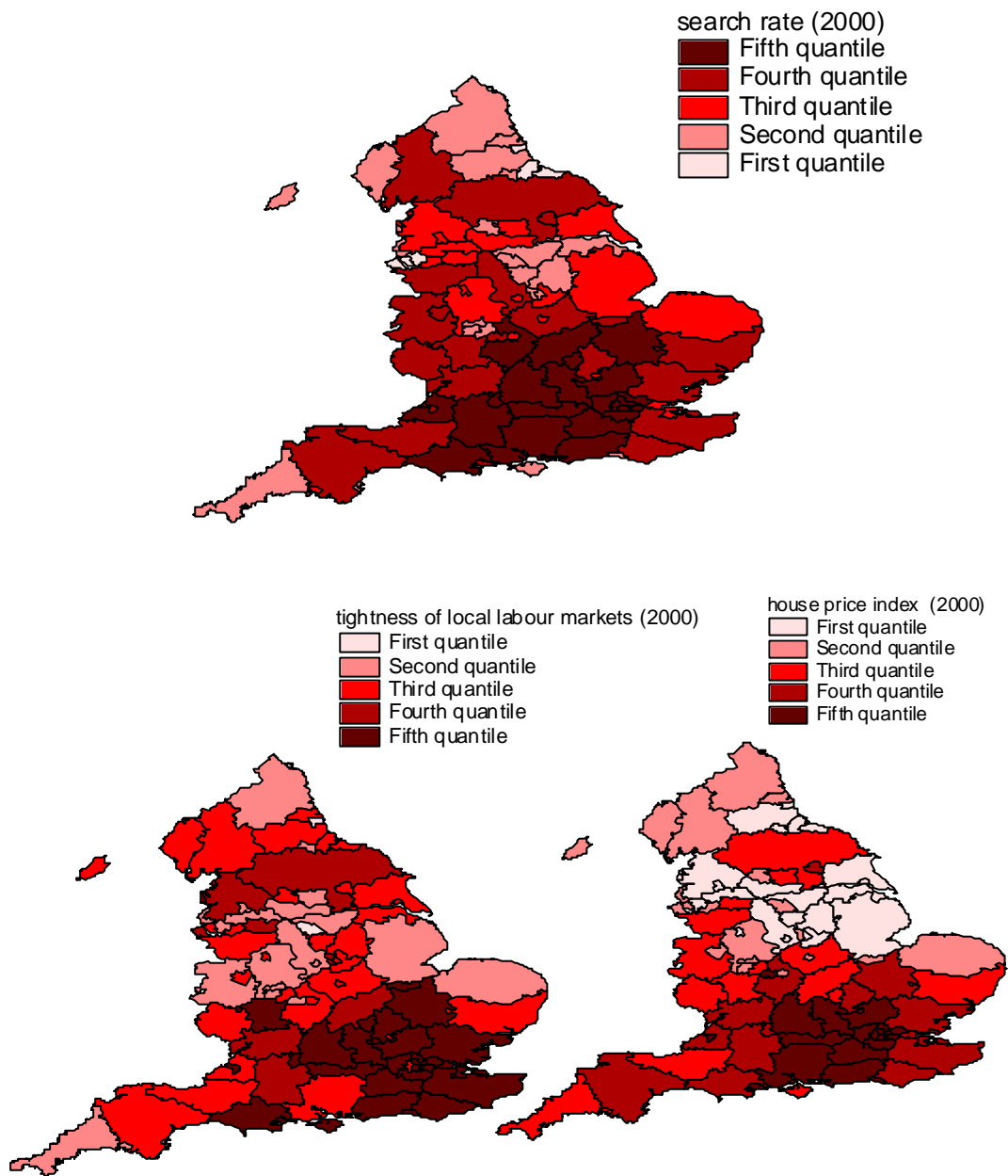


Figure 1: Quantiles maps

3.1 Data

Our empirical analysis is based on NUTS3 level data in England.³ The main data source is the Labour Force Survey (LFS hereafter). Given an area, the key variables under investigation are the (average) search intensity, the local cost of living and the local labor market tightness.

We define the average search intensity in area i , \bar{s}_i , as the ratio between active job seekers, and the sum of active job seekers and inactive persons living in the area.⁴ 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.

The other key variable in the theoretical model, the average cost of living in area i , h_i , is measured by a house price index. We are aware that the interactions between the labor market and the housing market are far more complicated (see e.g. Hughes and McCormick, 2000, Cameron and Muellbauer, 2001). However, because there is no complete set of sub-regional price indices for the UK, the main (and possibly the only) source of variation in prices within regions is differences in house prices. Furthermore, we exclude home-owners so that we rule out the possibility individuals can consider houses as assets.

Finally, the last variable of theoretical interest is the local labor market tightness θ_i . The National On-line Manpower Information Service (NOMIS) provides information of the labor market tightness at the county level.

In order to control for differences in skill composition, population structure, economic activity, sectorial composition, income and wealth, ethnic composition, job access, car access, agglomeration effects, social networks among NUTS3 areas, we include as regressors in our empirical model indicators of

³The 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.

⁴The 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).

education, age, economic activity, employment by occupation, indices of earnings by occupation and home ownership, ethnicity, (time) distance to jobs, motor vehicle usage, population density, main method of job search of people living in the area respectively.⁵ For a complete description of all the data, see Appendix 2.

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 (where the weights are the share of each occupation in total UK employment). 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 (where the weights are the share of each type of houses sales in total UK sales of houses). 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.⁶ Precise definitions of all variables used in the empirical analysis can be found in Appendix 2. Table 1 contains the summary statistics.

⁵Because the LFS sub-regional data are made available only starting from spring 2000 and earnings data are only available until year 2000, all 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: <http://www.nomisweb.co.uk/>) or in the ESRC Data Archive (www.data-archive.ac.uk) with the exception of house prices, that are available on line from the HM Land Registry (<http://www.landreg.gov.uk/>).

⁶Some NUTS3 areas have been aggregated due to lack of data on some of the variables. Also, all the empirical analysis presented in the paper has been performed excluding London before the housing market is quite peculiar.

Table 1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min.	Max.
\bar{s}	85	0.61	0.38	0	1
h	85	78.99	43.7	34.6	179.89
θ	85	0.2	0.18	0.05	1.2
\bar{t}^*	85	48.9	36.5	5	150
\bar{c}	85	67.8	27.79	33.76	91.06
\bar{u}	85	46.66	29.97	9.99	65.32
h_ow	85	61	20.18	10.1	92.4
d	85	893.98	1409.8	14.8	9950.01
<i>network</i>	85	58.01	7.57	9.2	72.2
<i>whites</i>	85	84.64	8.57	75.99	98.06
a	85	84.04	4.62	72.33	91.01
<i>skills3+</i>	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

* This time corresponds to a return trip in minutes.

3.2 Statistical model and estimation results

We use a regression model with a spatial autoregressive process for the error term. We write the model by separating the target variables from the other control variables for sake of clarity:⁷

$$\bar{s} = \delta h + \gamma \theta + X\beta + \varepsilon, \quad (18)$$

$$\varepsilon = \lambda P\varepsilon + \xi \quad (19)$$

⁷Theoretical details on the spatial error model can be found, among others, in Anselin (1988).

where \bar{s} , h and ϑ are $N \times 1$ vectors of observations ($N = 85$, the number of areas considered) on the search rate, cost of living and labor market tightness respectively, 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 .⁸

The choice of a regression model that controls for *spatial dependence* is motivated by statistical consideration. Indeed, the estimation of a standard regression model with diagnostics for spatial effects provides strong evidence of the presence of spatial dependence (see Appendix 4 for a detailed analysis on this issue).⁹ Thus, in order to assess correctly the significance of the coefficients of the variables of interest, this spatial dependence cannot be neglected.

On the other hand, the use of a *spatial error model* instead of a spatial lag model is motivated by economic considerations. Indeed, from a behavioral perspective, it makes little sense to estimate a spatial lag model in the context of our model since it implies that search decisions of workers in different spatial areas are jointly determined. On the other hand, 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.¹⁰

As a result, we estimate the spatial error model (18)-(19). The Maximum Likelihood estimation results (ML) on the target variables are reported in Table 2, second column.¹¹ For comparison purpose, the first column of this table display the OLS estimates that are obtained by estimating equation (18) assuming spherical disturbances. A complete statistical analysis of model (18)-(19), including estimation results for control variables and hypotheses tests, is

⁸The $N \times N$ matrix $P = \{p_{ij}\}$ is sometimes called contiguity matrix in the spatial statistics literature. It describes the geographical arrangement of the spatial units.

⁹In fact, a feature often neglected in regional studies, where the units have a spatial connotation, is the possible cross-sectional dependence of the residuals.

¹⁰We are grateful to Jan Bruecker for providing this example.

¹¹For details on the adaptation of the Maximum Likelihood estimator to this spatial case and on the estimation procedure see, among others, Anselin (1988).

contained in Appendix 4.¹² We conclude that the spatial error model defined by (18)-(19) appears to be appropriate and correctly specified.

Let us now focus on the interpretation of the Maximum Likelihood estimation results (column two of Table 2).

Table 2: Estimation Results - Target variables -

	OLS (standard regression model)	ML (spatial er- ror model)
<i>cons</i>	7.453** (3.7265)	5.982** (2.5029)
<i>h</i>	0.0889** (0.0362)	0.0928*** (0.0311)
<i>θ</i>	0.2402*** (0.076)	0.2354*** (0.0655)

*** significant at 1%

** significant at 5%

Control variables are included (see Table 4 in Appendix 4 for the complete results)

As predicted by the theoretical model, *both the (local) cost of living h and the (local) labor market tightness θ are found to have a positive and significant effect on unemployed search activity.* To be more precise, a unit increase in the cost of living in a county implies an increase of 0.09 in average search intensity in the area;¹³ a unit increase in the average level of labor market tightness θ increases search effort by 0.24.¹⁴

¹²All the estimation results have been obtained using SpaceStat version 1.80 (Anselin, 1995).

¹³Observe that, because the proxy used for (local) living costs is (local) house prices and not an index of all the consumption goods, the effect of the cost of living on search intensity should be smaller. However, since housing constitutes an important part of the household expenses, the difference should not be large.

¹⁴Different specifications of the empirical model and estimation methods are also been considered. First, in order to control for a potential reverse causality between local search rate and local cost of living this model specification has also been estimated instrumenting the houses prices by taking the historical prices. The first period of the available series, last term of 1998, has been used as instruments. Also, lag values of the labor market tightness have been used as instruments for the values of the variable at time t to account for a

4 Conclusion

In this paper, we examine the link between the local search activity of unemployed workers and residential characteristics, namely the local cost of living and local labor market tightness. We first develop a model that shows why areas with large cost of living and/or high labor market tightness are characterized by high levels of search activities. The intuition is quite simple. When the cost of living increases, workers consume less and thus have more leisure both when they are employed and unemployed. However, because the employed are assumed to value more leisure than the unemployed, the difference in intertemporal utility between the employed and the unemployed increases, and as a result, the unemployed workers search more actively because the reward of a successful match is higher. Similarly, when the labor market tightness

possible endogeneity issue. Second to investigate the importance of unobserved heterogeneity between areas and measurement errors in observed variables, we estimated a spatio-temporal model specified as a typical dynamic panel data model. The available data prevent us to perform a panel data analysis using a complete set of controls variables. We use all the nine waves of the BHPS to construct the local search rate and we estimated the following space-time autoregressive model:

$$\begin{aligned}\bar{s}_t &= \rho\bar{s}_{t-1}^* + \lambda P\bar{s}_t^* + \delta h_t^* + \gamma\vartheta_t + \eta + \varepsilon, \\ \bar{s}_t^* &= \bar{s}_t + m_t, \\ h_t^* &= h_t + m_t, \quad t = 1, \dots, 9,\end{aligned}$$

where the same definitions of model (18)-(19) apply, with the difference that ε is now a white noise disturbance term and as proxy for the cost of living, h , the Halifax price index (all data available on line: <http://www.hbosplc.com/view/housepriceindex/housepriceindex.asp>) has been used, because it is available at sub-regional level for a longer time period. In addition, \bar{s}_{t-1} is the time lag for the search rate, η is a vector of time invariant area specific fixed effects, variables denoted by * represent the true latent variables and m_t is a measurement error, assumed to follow different stochastic processes. After controlling for spatial dependence in the data by choosing an appropriate order in the spatial process, the literature on dynamic panel data models can be used. The model can be estimated using an instrumental variables approach within a Generalized Method of Moments (GMM) estimation procedure (Arellano and Bond (1991)). Distributional assumptions are not needed. Different specifications for the measurement errors in observed variables can be taken into account by using sufficiently lagged variables as instruments.

For the purpose of this paper, i.e. the empirical test of the theoretical model, the interesting result is that the estimation results related to the target variables (that is positive and significant estimated coefficients of local cost of living and local labor market tightness) remain qualitatively unchanged across all the model specifications and estimation methods used.

rises, it becomes easier to find a job (there are relatively more jobs available compared to the unemployed) and thus the returns to search are higher. As a result, workers put more effort in search activities.

We then test these predictions on sub-regional data in England for the year 2000 using a spatial lag model. Both the local cost of living and the local labor market tightness are found to have a positive and significant effect on the average unemployed labor market participation. These findings are consistent with the prediction of the theoretical model.

We believe that these results have important implications for regional policies. Indeed, workers seem to search more actively in areas for which both costs of living and labor market tightness are quite high. If we look again at the maps described in Figure 1, then, not surprisingly, in England, these areas are located in the southern part of the country. This suggests that policies that aim at reducing local unemployment should be more active in the North by, for example, subsidizing housing or inducing firms to set up there. This is reinforced by the fact that spatial correlation is quite strong, i.e. high-search intensity areas are in general adjacent to areas with the same characteristics. This suggests that a relevant issue for future research could be to investigate more closely the spatial interdependence between local labor markets.

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Appendix 1: Proofs of propositions

Proof of Proposition 1

Before proving this proposition, let us state the following Lemma.

Lemma 1 *There exists a unique solution s_k^* to the first order condition (16).*

Proof. By totally differentiating (16), we obtain the following second order condition:

$$\begin{aligned} SOC &= \frac{\partial^2 V^0}{\partial s_k^2} + \frac{M(\bar{s}, \theta)}{\bar{s}} \frac{\partial (W^1 - W_k^0)}{\partial s_k} \\ &= -(1 - \alpha^0) \frac{C''(s_k)(b - C(s_k)) + [C'(s_k)]^2}{[b - C(s_k)]^2} + M(\bar{s}, \theta) \frac{\partial (W^1 - W_k^0)}{\partial s_k} \end{aligned}$$

Using (15) and (16), it is easy to check that

$$\frac{\partial (W^1 - W_k^0)}{\partial s_k} = 0$$

so that

$$\begin{aligned} SOC &= \frac{\partial^2 V^0}{\partial s_k^2} \\ &= -\alpha^0 \frac{1}{(1 - s_k)^2} - (1 - \alpha^0) \frac{C''(s_k)(b - C(s_k)) + [C'(s_k)]^2}{[b - C(s_k)]^2} \end{aligned}$$

Now, because $C''(s_k) > 0$, all the terms of SOC are negative and thus $SOC < 0$. ■

Let us now prove Proposition 1.

First, observe that, at the symmetric equilibrium where $s_k^* = \bar{s}^*$, (15) is equivalent to

$$W^1 - W_k^0 = \frac{V^1 - V^0}{r + \delta + M(\bar{s}^*, \theta)}$$

with

$$\begin{aligned} V^1 &= \alpha^1 \log(1 - T) + (1 - \alpha^1) \log\left(\frac{wT}{h}\right) \\ V^0 &= \alpha^0 \log(1 - s_k) + (1 - \alpha^0) \log\left(\frac{b - C(s_k)}{h}\right) \end{aligned}$$

We have

$$\frac{\partial (W^1 - W_k^0)}{\partial h} = \frac{1}{h} \frac{(\alpha^1 - \alpha^0)}{r + \delta + M(\bar{s}, \theta)} > 0 \quad (20)$$

$$\frac{\partial (W^1 - W_k^0)}{\partial \theta} = -\frac{V^1 - V^0}{[r + \delta + M(\bar{s}, \theta)]^2} \frac{\partial M(\bar{s}, \theta)}{\partial \theta} < 0 \quad (21)$$

Let us first prove (i). By totally differentiating (16), we easily obtain:

$$\frac{\partial s_k^*}{\partial h} = -\frac{1}{SOC} \left[\frac{M(\bar{s}, \theta)}{\bar{s}} \frac{\partial (W^1 - W_k^0)}{\partial h} \right]$$

which, by using (20), is equivalent to:

$$\frac{\partial s_k^*}{\partial h} = -\frac{1}{SOC} \left[\frac{1}{h} \frac{M(\bar{s}, \theta)}{\bar{s}} \frac{(\alpha^1 - \alpha^0)}{r + \delta + M(\bar{s}, \theta)} \right]$$

where SOC , the second order condition, is strictly negative by Lemma 1 and $\alpha^1 > \alpha^0$ by assumption. Thus

$$\frac{\partial s_k^*}{\partial h} = \frac{\partial \bar{s}^*}{\partial h} > 0$$

Let us now prove (ii). By totally differentiating (16) and by using (3), we easily obtain:

$$\frac{\partial s_k^*}{\partial \theta} = -\frac{1}{SOC} \frac{1}{\bar{s}} \left[\frac{\partial M(\bar{s}, \theta)}{\partial \theta} (W^1 - W_k^0) + M(\bar{s}, \theta) \frac{\partial (W^1 - W_k^0)}{\partial \theta} \right]$$

The sign of $\frac{\partial s_k^*}{\partial \theta}$ is thus the same as the sign of

$$\frac{\partial M(\bar{s}, \theta)}{\partial \theta} (W^1 - W_k^0) + M(\bar{s}, \theta) \frac{\partial (W^1 - W_k^0)}{\partial \theta}$$

By using (21), we have:

$$\begin{aligned} & \frac{\partial M(\bar{s}, \theta)}{\partial \theta} (W^1 - W_k^0) + M(\bar{s}, \theta) \frac{\partial (W^1 - W_k^0)}{\partial \theta} \\ &= \frac{\partial M(\bar{s}, \theta)}{\partial \theta} (W^1 - W_k^0) - M(\bar{s}, \theta) \frac{V^1 - V^0}{[r + \delta + M(\bar{s}, \theta)]^2} \frac{\partial M(\bar{s}, \theta)}{\partial \theta} \\ &= \frac{\partial M(\bar{s}, \theta)}{\partial \theta} \left[\frac{V^1 - V^0}{r + \delta + M(\bar{s}, \theta)} - M(\bar{s}, \theta) \frac{V^1 - V^0}{[r + \delta + M(\bar{s}, \theta)]^2} \right] \\ &= \frac{\partial M(\bar{s}, \theta)}{\partial \theta} \frac{V^1 - V^0}{r + \delta + M(\bar{s}, \theta)} \left[\frac{r + \delta}{r + \delta + M(\bar{s}, \theta)} \right] > 0 \end{aligned}$$

As a result

$$\frac{\partial s_k^*}{\partial \theta} = \frac{\partial \bar{s}^*}{\partial \theta} > 0$$

■

Appendix 2: Description of variables

\bar{s} : Ratio between unemployed and job seekers currently unavailable to start working without a valid reason (not home-owners), and unemployed, job seekers currently unavailable and inactive persons (not home-owners). Source: LFS-INECA variable. It is a derived variable which classifies the individual economic activity according to the ILO standard definitions.

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

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

\bar{t} : Ratio between total time spent travelling to jobs by employed workers, and total number of employed. Source: LFS

\bar{v} : Ratio between active job seekers owning or using a motor vehicle, and total number of active job seekers. Source: LFS.

\bar{u} : Ratio between workers who have been unemployed for more than one year and the total number of unemployed. 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)¹⁵ 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)¹⁶ over total number of employed. Source: LFS

¹⁵The 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/>.

¹⁶The 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.

(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).

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

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.

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 :

$$I_{iq} = \frac{\sum_{j=1}^Q w_{ij} \bar{\eta}_j}{\sum_{j=1}^Q w_{UKj} \eta_{UKj}}, \quad q = 1, \dots, 4$$

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

$$\bar{\eta}_j = \frac{\eta_{UKj}}{\eta_{UK}},$$

- η_{UKj} = employed in sub group j in UK,
- η_{UK} = total employed in UK,
- w_{ij} = average hourly wage of employed in sub group j in area i ,
- w_{UKj} = average hourly wage of employed in sub group j in UK.

Similarly, the house price index is constructed as follow.

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

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

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

$$\bar{\eta}_j = \frac{\eta_{UKj}}{\eta_{UK}},$$

- η_{UKj} = sales of houses of type j in UK,
- η_{UK} = total sales of houses in UK,
- P_{ij} = average price of houses of type j in area i ,
- P_{UKj} = average price of houses of type j in UK.

Appendix 4: Regression diagnostics

In this appendix we provide evidence that the statistical models defined by (18)-(19) is appropriate and correctly specified, and the complete list of estimation results.

Let us consider Table 3. It has the same structure than Table 2 (results for the spatial error model in the second column and for the classical regression model in column one) and it reports measures of fit and hypotheses tests. 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 error model (column two and four), obviously we do not find the statistic T_1 (normality is assumed) and T_4 (there is no spatially lagged dependent variable included in the model specification), there is still a Breusch-Pagan test against heteroskedasticity (T_2) and a test on the spatial error autoregressive coefficient (T_3), which is a Likelihood Ratio test in this case. In addition, we also find a Likelihood Ratio test (T_5) and a Wald test (T_6) on the common factor hypothesis. These last two tests verify if the coefficients satisfy the restrictions needed to guarantee the consistency of the spatial error specification. All the statistics are asymptotically distributed as a chi-squared. They differ in terms of degrees of freedom. The T_1 statistic presents two degree of freedom, both T_3 and T_4 statistics have one degree of freedom and T_2 , T_5 and T_6 have as many degrees of freedom as the number of regressors in the model.¹⁷

Let us focus our attention on the analysis of the specification of model (18)-(19). Looking at the diagnostics in column one (classical regression model), the hypothesis of normality of the errors cannot be rejected (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. The T_2 statistic is not significant, providing no evidence of heteroskedasticity. On the contrary, both tests for spatial dependence (T_3 and T_4)

¹⁷For more details and a technical discussion of model validation in spatial regression models (measures of fit and specification diagnostics), see Anselin (1995).

are highly significant, indicating clearly the presence of spatial dependence ignored in the model. Although the T_4 statistic is slightly more significant than the T_3 statistic, there is no clear indication to conclude which is the proper alternative spatial model to use (spatial lag model or spatial error model).¹⁸ As discussed in Section 3.2, we choose the spatial-error model on the basis of economic considerations.

Looking at column two (spatial error model), we can observe that the performance of the spatial model has been improved with respect to the standard regression model (column one) and it appears correctly specified. In fact, if we compare the values of LIK, AIC and SC for this spatial model with the ones reported in the first column (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. Furthermore, the T_2 statistic is still not significant, providing evidence that there is no ignored heteroskedasticity in the model, the T_3 statistic is highly significant and neither T_5 nor T_6 are significant, indicating that the spatial error specification is appropriate.

If we compare the parameters estimates and associated standard errors in column one and two of Table 2 (i.e. OLS of the standard regression model and ML of the spatial error model), the point estimates are similar but there is a gain in precision of the estimated coefficients using a spatial error model.¹⁹

For completeness, Table 4 contains the estimation results for the control variables. Quite intuitively, the search behavior of job seekers living in an area appear to be positively and significantly affected by the activity rate, the percentage of young people and negatively and significantly by the percentage of old people and by the percentage of long-term unemployed in the area. Interestingly, we also find that having access to a private motor vehicle has a positive and significant effect on search intensity and that, on the other hand, (time) distance to jobs has a negative and significant effect. These findings suggest an important role of transport mode in shaping job seekers search effort decisions.

¹⁸Note that they are asymptotic tests whereas we deal with a small data set.

¹⁹Note that the consequences of ignoring spatial error dependence are not severe. OLS estimators are still unbiased. However, they are inefficient. Indeed, also using OLS estimators our our main results, i.e. the positive and significant effect of cost of living and labor market tightness on search intensity are qualitatively the same. The spatial error model has been estimated mainly for robustness check.

Table 3: Measures of fit and Hypotheses tests

	OLS	ML
	(standard regression model)	(spatial error model)
LIK	-110.12	-103.78
AIC	264.24	251.55
SC	317.97	305.29
T_1	3.366	
(2)	[0.1858]	—
T_2	26.734	25.887
(21)	[0.1798]	[0.2108]
T_3	8.88	11.13
(1)	[0.0029]	[0.0008]
T_4	9.04	
(1)	[0.0026]	—
T_5		27.98
(21)	—	[0.1407]
T_6		29.16
(21)	—	[0.1102]

Notes:

- degrees of freedom in parentheses
- p-value in squared brackets

Table 4: Estimation Results -complete model-

	OLS (standard regression model)	ML (spatial error model)
<i>cons</i>	7.453** (3.7265)	5.982** (2.5029)
<i>h</i>	0.0889** (0.0362)	0.0928*** (0.0311)
θ	0.2402*** (0.076)	0.2354*** (0.0655)
\bar{t}	0.0063** (0.0027)	0.0071** (0.0028)
\bar{c}	0.0579** (0.0274)	0.0675*** (0.0232)
\bar{u}	-0.0746** (0.0337)	-0.0829*** (0.0297)
<i>skills3+</i>	-0.0336 (0.9542)	-0.0268 (0.9143)
<i>a</i>	0.3232** (0.1524)	0.3825** (0.1567)
<i>y16 - 24</i>	0.5561** (0.2386)	0.5442** (0.2203)
<i>y25 - 49</i>	0.5471 (1.339)	0.4561 (1.3227)
<i>y50 - 64</i>	-0.1017* (0.0538)	-0.1402** (0.0631)
<i>e_123</i>	0.9411 (0.8933)	0.8641 (0.8532)
<i>e_67</i>	-0.0254 (0.0288)	-0.017 (0.0208)
<i>e_89</i>	0.0435 (0.1671)	0.0413 (0.1452)
<i>whites</i>	0.092 (0.0663)	0.1002 (0.0701)
<i>network</i>	0.0102 (0.0995)	0.0224 (0.0951)

w_{123}	-0.0101 (0.0226)	-0.0062 (0.0227)
w_{45}	0.0065 (0.0169)	0.0098 (0.0116)
w_{67}	0.0011 (0.0087)	0.002 (0.0083)
w_{89}	0.001 (0.0231)	0.0005 (0.0268)
d	0.0006 (0.0216)	0.0007 (0.0201)
h_{ow}	0.0724 (0.0972)	0.0617 (0.0871)
λ	-	0.667*** (0.1797)

- *** significant at 1%
- ** significant at 5%
- * significant at 10%

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