How Local Are Labor Markets?
Evidence from a Spatial Job Search Model*

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June 2015

Abstract

This paper models the optimal search strategies of the unemployed to characterize local labor markets. Our methodology allows for linkages between numerous areas, while preserving tractability. We estimate that labor markets are indeed ‘local’, as the attractiveness of jobs to applicants sharply decays with distance. Also, workers are discouraged from searching in areas with strong job competition from other jobseekers. As labor markets overlap, local stimulus has modest effects on local outcomes, because ripple effects in job applications dilute its impact across space. Hiring subsidies for the locals are instead more effective, because they improve locals’ chances in the competition for jobs.

Keywords: job search; local labor markets; place-based policies; ripple effects.
JEL classification: J61; J63; J64; R12.

*We wish to thank Stéphane Bonhomme, Gilles Duranton, Pat Kline and seminar participants at the London School of Economics, Paris School of Economics, CREST (Paris), University of Toulouse, the University of Essex, City University, Rome Tor Vergata, the NBER Summer Institute Labor Studies 2010, the NBER Summer Institute Macro Perspectives 2011, the CEPR ESSLE Conference 2010, the Bank of Portugal Conference on Wages, Job Turnover and Education 2011, the Cergy-Pontoise Conference on Labor Markets 2011 and LACEA Conference 2013 for helpful comments. We also thank Timothée Carayol for excellent research assistance.
1 Introduction

How local are labor markets? A number of important questions in labor economics turn on the answer. In recent years there has been a resurgence of interest in the consequences of localization of economic activity for workers’ welfare (Moretti, 2011) and in policies aimed to improve labor market outcomes in disadvantaged areas (see Glaeser and Gottlieb, 2008, for a survey, and recent work by Busso, Gregory and Kline, 2013). In the US, federal, state and local governments combined spend nearly $50 billion per year on local development policies. These policies crucially rely on available measures of the size of local labor markets to design appropriate intervention. If labor markets are very local, an effective intervention needs to be targeted to the disadvantaged areas themselves. But if labor markets are not as local, targeted intervention is ineffective insofar as it simply attracts workers from other, more advantaged areas. A broader but related question concerns the incidence of local shocks to labor demand and their impact on labor mobility and labor market equilibrium (see among others Blanchard and Katz, 1992, Bound and Holzer, 2000, and Notowidigdo, 2011). This whole body of research needs a clear definition of a ‘place’.1

Most academic research on the topic and government statistical agencies divide geographical space into a relatively small number of non-overlapping areas, which are assumed to be self-contained labor markets. In other words, workers are implicitly assumed to freely travel within them when looking for work but cannot – without moving residence – accept a job in a different labor market. Examples would be the BEA’s 179 Economic Areas and the 720 Commuting zones for the US, or the 320 Travel to Work Areas (TTWAs) for the UK. While these efforts are understandable and useful, they have important limitations. First, the cost of distance within such areas is assumed away. Because people commute from large distances to work in the centre of big cities, large metropolitan areas are generally classified as single labor markets. But those who live in the northern suburbs may not think of the far southern suburbs as part of ‘their’ labor market. Second, the non-overlapping nature of local labor markets constructed in this way causes inevitable discontinuities around the boundaries. Someone living just inside a large metropolitan area would be classified as living in a large labor market, while someone living just across the border would be classified as living in a modestly-sized labor market, while in reality these people are in essentially the same labor market.

The fundamental cause of these problems is a failure to recognize that the economy cannot be divided into non-overlapping segments, as the labor market for one individual at one location overlaps with that for another individual in a different but not too distant

1 Another related issue is the spatial mismatch hypothesis (Kain, 1968), suggesting that the unemployment rate of blacks in the inner city was so high because many jobs had moved to the suburbs and these jobs were no longer in the local labor market of those living in the city (see also Hellerstein, Neumark and McInerney, 2008, and Boustan and Margo, 2009, and Zenou, 2013, for recent studies).
location. This has key implications for modeling local labor markets and for understanding the impact of local policies.

This paper proposes a more realistic approach to model local labor markets, while preserving tractability. To this purpose we build a job search model which provides an explicit microfoundation for the linkages between (a very large number of) areas. Jobseekers decide whether to apply to job vacancies at different locations, based on the cost of distance to target jobs and on the expected success rate of their applications, in turn depending on how many other jobseekers across the economy find these jobs attractive. Inter-dependencies across areas arise because the number of applicants to jobs in a given area is likely to be influenced (even if only very slightly) by unemployment and vacancies in all other areas, as they are ultimately linked through a series of overlapping markets. Key parameters of this framework are the rate of decay of the utility obtained from a job with the distance from the job location, and the way in which job competition in an area discourages jobseekers from applying to jobs within the area.

Our empirical application divides the UK labor market into 8850 small neighborhoods, corresponding to Census wards. Despite the fact that workers in one of 8850 locations can apply to jobs in one of 8850 locations – so there are over 78 million possibilities – and the decision of each worker is influenced by the search strategies of other workers, we show that the equilibrium allocation of applications can be solved for using an efficient contraction mapping. This makes estimation of our matching model feasible, in spite of a much larger number of areas than in other, related applications (see for example the gravity models of Eaton and Kortum, 2002).

While there are no distinct labor markets in our set-up, it is natural to use the estimated cost of distance as a measure of the effective size of local labor markets, as this is a key determinant of the set of jobs that an unemployed worker, currently in a particular location, is willing to apply for. Our estimates indicate a relatively high cost of distance, implying that the probability of a random job 5km distant being preferred to a random job in the worker’s own ward is only 11%. Also, workers are discouraged from applying to jobs in areas where they expect relatively strong competition from other jobseekers. An interesting side result is that constant returns in search markets are not rejected, implying that larger-scale markets would not systematically offer more efficient matching of workers to jobs. The estimated model predicts commuting patterns across UK wards which replicate fairly accurately actual commuting patterns obtained from the 2001 Census, although it tends to underpredict the proportion of individuals who live and work in the same ward. Finally, we find that, although the labor market for any given individual worker is indeed quite ‘local’, location-based policies in the form of local stimulus to labor demand or improved transport links are rather ineffective in raising the local job finding rate, because labor markets for individual workers overlap and the associated ripple effects in job applications largely dilute
the impact of local policies across space. This result could not be achieved if labor markets were modeled as non-overlapping. However, the combination of local stimulus with explicit hiring subsidies for the ‘locals’ is more effective because it improves the locals’ chances in the competition for jobs.

The plan of the paper is as follows. The next Section describes the data used and Section 3 presents reduced-form estimates of a matching function which encompasses geographic spillovers. We argue that such specifications offer only limited insight about the size of local labor markets, and in Section 4 we propose a model of job search across space, illustrating that the size of labor markets can be inferred from the optimal search strategies of the unemployed. Section 5 reports our main estimates and several robustness tests. Section 6 uses the model estimates to illustrate the simulated impact of location-based policies on the spatial distribution of the unemployment outflow. Section 7 concludes.

2 Data and descriptive statistics

We use data on unemployment and vacancies, disaggregated at the Census ward level (CAS 2003 classification). These data are available on NOMIS (nomisweb.co.uk) and run monthly since April 2004. There are 10,072 wards in Great Britain, of which 7,969 in England, 881 in Wales, and 1,222 in Scotland, with an average population of 5,670. Although unemployment and vacancy data are available for Scottish wards, commuting data, which we also use below, are not, and thus we restrict our sample to the 8,850 wards in England and Wales.²

Our data cover registered unemployment (the ‘claimant count’) and job vacancies advertised at the UK Public Employment Service. The UK PES is structured as a network of government funded employment agencies (Jobcentre Plus), whereby each town or neighborhood within a city has at least one Jobcentre. Jobcentre services are free of charge both to jobseekers and employers. To be entitled to receive welfare payments, unemployed benefit claimants are required to register at a Jobcentre, and ‘sign-on’ every two weeks. It is worth noting that the UK PES is much more widely used than its US equivalent (see Manning, 2003, Table 10.5), and OECD, 2000).

Employers wishing to advertise job vacancies submit a form with detailed job specifications to a centralized service called Employer Direct. The job vacancy is then assigned to the employer’s local Jobcentre, and will have a dedicated recruitment adviser, who can assist the employer with the recruitment process. Regardless of the Jobcentre in charge, the Census ward for each vacancy is defined using the full postcode of the job location. Each job vacancy is advertised in three ways: on the centralized employment website www.direct.gov.uk; through the Jobcentre Plus phone service for job applicants; and on the Jobcentre Plus

²Because the border between England and Scotland is very sparsely populated, local labor markets in England can be safely regarded as distinct from local labor markets in Scotland.
network, which can be accessed at Jobcentre offices around the country. Jobseekers can sample job openings via one or more of these methods, using various search criteria (sector, occupation, working hours, distance from a given postcode etc.). The detailed geographic information on both claimant unemployment and job vacancies recorded at Jobcentres makes them a unique data source for studying job matching patterns at the very local level. While the monthly series run from April 2004 onwards, we restrict our sample period to April 2004-April 2006, because from May 2006 Jobcentre Plus introduced changes to its vacancy handling procedures, and the vacancy series since May 2006 are less suitable for our purposes.3

As not all jobseekers are claimant unemployed and not all vacancies are advertised through the PES, our data cannot cover all job matching activity in the economy. Appendix A provides some detailed discussion of data coverage, and shows that do we capture an important section of both supply and demand of the job search process in the UK, especially for low-skilled workers and jobs. But imperfect coverage would introduce a bias if the portion of the job search process covered by our data varies systematically across areas, something on which unfortunately we have no information. As a check against the possibility of biases we also investigate how accurately our model of job search explains the commuting flows across wards using census data that covers everyone in employment, independently of how they searched for jobs.

In the data presented below and in all estimated specifications, we obtain the vacancy and unemployment outflows as differences between the corresponding inflows and the monthly variations in the stocks. For the unemployed, the outflow series predicted by the stock-flow accounting identity is virtually identical to that reported, while for vacancies the correlation is 0.81. Such discrepancy may arise because the reported outflow does not include cases of “suspended” vacancies, or cases of vacancies “awaiting follow-up”, but these may well be cases of positions being filled without keeping the Jobcentre informed. Due to measurement error, for about 0.5% of observations the vacancy outflow implied by the stock-flow accounting identity is negative, and we drop the corresponding observations.

Table A1 of the Appendix presents some simple descriptive statistics on unemployment and vacancies stocks and flows from May 2004-April 2006, a period of historically low and stable unemployment.4 English wards have on average 106 unemployed and 91 vacancies per month. Taken across the whole period, both unemployment and vacancy inflows and

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3Prior to May 2006, vacancies notified to Jobcentre Plus were followed up with the employer until they were filled, and the number of vacancies filled at a Jobcentre was used as one of the main indicators of its performance. From May 2006, the Jobcentre Plus performance evaluation is no longer based on vacancies being filled, thus vacancies notified to Jobcentre Plus are not followed-up, and have an ex-ante closure date agreed with the employer, upon which they are automatically withdrawn. This systematically understates the stock of existing vacancies from May 2006 onwards.

4We lose the initial month in the sample period because we need lags of the vacancy and unemployment stock measures, i.e. values measured at the end of the previous month.
outflows are very similar. There is also very wide spatial variation in unemployment and vacancies, which may be best grasped on a map. Figure A1 shows spatial variation in the unemployment-to-vacancy ratio for a representative month in our sample, February 2005. Different wards are shaded according to the quartile of the corresponding U-V ratios, with darker shades corresponding to higher quartiles. The striking feature that emerges from this map is that there is no simple pattern – rather we observe a patchwork of very different labor market outcomes across quite small areas, e.g. many high-unemployment wards are adjacent to low-unemployment wards so that one cannot detect one large region in which, say, all high-unemployment wards are clustered together.

3 Estimates of a Reduced-Form Matching Function

We start investigating the data by estimating a conventional log-linear matching function. As is standard in the empirical matching function literature (see, for example, Petrongolo and Pissarides, 2001) we estimate a specification which regresses a measure of the matching rate (the vacancy outflow rate in our application) on the stocks of unemployment and vacancies. Due to geographic spillovers, the relevant stocks include those measured in the local and surrounding areas, and we capture this idea in the following specification:

\[
\log \left( \frac{M_{b,t}}{V_{b,t}} \right) = \alpha_0 + \alpha_1 \log(U_{b,t} + \beta_1 U_{5b,t} + \beta_2 U_{10b,t} + \beta_3 U_{20b,t} + \beta_4 U_{35b,t}) \\
+ \alpha_2 \log(V_{b,t} + \gamma_1 V_{5b,t} + \gamma_2 V_{10b,t} + \gamma_3 V_{20b,t} + \gamma_4 V_{35b,t}) + \epsilon_{b,t},
\]

(1)

where \( M_{b,t} \) is the vacancy outflow from ward \( b \) at time \( t \), \( U_{b,t} \) is the number of unemployed in ward \( b \), \( U_{5b,t} \) is the number of unemployed in wards within 5km of \( b \) (excluding \( b \) itself), \( U_{10b,t} \) is the number of unemployed in wards between 5km and 10km of ward \( b \) etc., and similarly for vacancies. The dependent variable is thus the vacancy outflow rate. This specification implies that the probability of filling a vacancy in \( b \) depends on local unemployment and on unemployment in the surrounding areas, whereby more distant unemployed workers are less effective in filling a vacancy in \( b \), i.e. we would expect \( \beta_i < 1 \). Similarly, more vacancies in area \( b \) and neighboring wards are expected to reduce the vacancy outflow rate in \( b \), but more distant vacancies have a smaller effect, i.e. we expect \( \gamma_i < 1 \). Specifications similar to (1) have been estimated by Burda and Profit (1996) for Czech districts, and Burgess and Profit (2001) and Patacchini and Zenou (2007) for UK TTWAs.

Next define the total number of unemployed and vacancies within 10km of \( b \) to be:

\[
\tilde{U}_{10b,t} = U_{b,t} + U_{5b,t} + U_{10b,t} ; \quad \tilde{V}_{10b,t} = V_{b,t} + V_{5b,t} + V_{10b,t} ;
\]
and approximate (1) by

$$\log \left( \frac{M_{b,t}}{V_{b,t}} \right) = \alpha_0 + \alpha_1 \log \tilde{U}_{10b,t}$$

$$+ \alpha_1 \left( \frac{1 - \beta_2}{\beta_2} \frac{U_{b,t}}{U_{10b,t}} + \frac{\beta_1 - \beta_2}{\beta_2} \frac{U_{5b,t}}{U_{10b,t}} + \frac{\beta_3 - \beta_2}{\beta_2} \frac{U_{20b,t}}{U_{10b,t}} + \frac{\beta_4 - \beta_2}{\beta_2} \frac{U_{35b,t}}{U_{10b,t}} \right)$$

$$+ \alpha_2 \log \tilde{V}_{10b,t}$$

$$+ \alpha_2 \left( \frac{1 - \gamma_2}{\gamma_2} \frac{V_{b,t}}{V_{10b,t}} + \frac{\gamma_1 - \gamma_2}{\gamma_2} \frac{V_{5b,t}}{V_{10b,t}} + \frac{\gamma_3 - \gamma_2}{\gamma_2} \frac{V_{20b,t}}{V_{10b,t}} + \frac{\gamma_4 - \gamma_2}{\gamma_2} \frac{V_{35b,t}}{V_{10b,t}} \right) + \varepsilon(2)$$

This specification has the advantage of being linear in parameters, so we can easily use instrumental variables and introduce ward fixed-effects. Moreover, returns to scale in the matching function can be simply assessed by comparing the coefficients on $\log \tilde{U}_{10b,t}$ and $\log \tilde{V}_{10b,t}$, while the coefficients on the share variables $U_{b,t}/\tilde{U}_{10b,t},..., U_{35b,t}/\tilde{U}_{10b,t}$, and $V_{b,t}/\tilde{V}_{10b,t},..., V_{35b,t}/\tilde{V}_{10b,t}$ indicate the relative effectiveness of unemployment and vacancies at different distances. The decision to ‘normalize’ by unemployment and vacancies within 10km is essentially arbitrary, but it is important to choose a normalization for which $\gamma_2$ and $\gamma_2$ are not zero, and for which the share variables are not too large. Considering this, 10km seemed the right choice. On average, about 5% of unemployment and vacancies within 10km are in the local ward, one-third are within 5km. Moving beyond the 10km ring, there are about 4.5 times the number of unemployed and vacancies between 10 and 20km as within 10km and 16 times as many within 35km.

Estimates of specification (2) are reported in Table 1. Column 1 pools all months and wards without time or ward effects. The estimates are in line with the typical matching function results in which the probability of filling any given vacancy rises with the number of unemployed and falls with the number of vacancies. The coefficients on the unemployment and vacancy variables imply a returns-to-scale parameter of 0.988, suggesting (something very close to) constant returns. This parameter is significantly different from one but this is likely a result of the large number of observations. It is not just the level of unemployment and vacancies within 10km that affect the outflow rate but also their geographical mix. As expected, the closer the unemployed to a ward, the higher the local vacancy matching rate. From the coefficients on the share of unemployment in the local ward and within 5km one can derive an estimate for $\beta_2$ of 0.22 and for $\beta_1$ of 0.53, i.e. unemployed workers outside the ward but within 5km have 53% of the effectiveness of generating matches as those within the ward and the unemployed in the 5-10km ring have an effectiveness of 22%. Unemployed in the 20km and 35km rings have tiny effects on the vacancy outflow, but statistically different from zero. For vacancies, the closer they are, the lower the local outflow rate, as jobs at shorter distances are are closer substitutes to local ones. Vacancies within 5km have 23% of the effectiveness of those within the ward, and vacancies in the 5-10km ring have an
effectiveness of 21%. Vacancies in the 20km and 35km rings have very small effects on the vacancy outflow rate. Column 2 introduces time dummies, with a very slight attenuation of all the coefficients, but virtually identical conclusions.

Our estimated models implicitly assume that the stocks of unemployment and vacancies can be treated as exogenous.\textsuperscript{5} While this is the standard approach in the empirical matching function literature, there are concerns that this may lead to biases in the estimates of interest. For example, innovations in matching efficiency in an area, as represented by $e_{h,t}$, would affect worker location and job creation, leading to an upward bias on the coefficients on both unemployment and vacancies. Furthermore, as the dependent variable is obtained by dividing the vacancy outflow by the local stock, which also appears in the construction of some of the right-hand side variables, a division bias issue may occur if the vacancy stock is measured with error. Column 3 thus instruments all vacancy and unemployment variables using the one-month lags in the corresponding inflows. The coefficients on the unemployment variables, as expected, are now lower – specifically the coefficient on $\log \hat{u}_{100,t}$ is only slightly lower, while the one on $u_{h,t}/\hat{u}_{100,t}$ is markedly lower – while the coefficients on vacancy variables are higher, consistent with a division bias, rather than an endogeneity bias. And indeed the coefficient which is mostly affected is the one on $v_{h,t}/\hat{v}_{100,t}$, on which the local vacancy stock has the most influence. Overall, our previous qualitative conclusions on matching elasticities $\alpha_1$ and $\alpha_2$, as well as on the decay of spillover effects with distance, are robust to the introduction of instrumental variables.

Column 4 introduces ward fixed effects and the most noticeable change is a marked increase in standard errors on all coefficients, as within-ward variation in unemployment and vacancy variables is smaller than the cross-section variation. This is especially true for unemployment variables, as within ward variation in (log) unemployment explains less than 3% of the total variance, while for (log) vacancies the within variation explains 12% of the total variance. The matching elasticities $\alpha_1$ and $\alpha_2$ remain firmly significant, but the spatial distribution of spillovers is no longer precisely identified. This implies that most of the useful variation in investigating spatial matching is cross-sectional and this will be exploited in our structural estimates.

The dependent variable in specification (2) is not defined when the outflow rate is zero. While this is not relevant for existing empirical studies of the matching function, because of their higher level of aggregation, it becomes a potential issue when using data on very small areas, and indeed the vacancy outflow is zero in 6.2% of observations in our sample. There are various approaches one might take to dealing with this. Below we estimate outflow

\textsuperscript{5}Existing evidence on residential migration of the unemployment is clearly in line with our assumption of exogenous jobseekers’ location. Gregg, Machin and Manning (2004) show that the unemployed in the UK rarely migrate in search of better job opportunities, and evidence suggests that those who both find a job and move location in a given year typically find a job first and then seek to move home if the commute from their current location is too unconvenient (Gregg, Machin and Manning, 2004, pp. 387-395).
equations like (2) in levels instead of logs. In the next section we derive a functional form in levels from an urn-ball model. The functional form used in this section has the disadvantage that the predicted value for the dependent variable is not restricted between zero and one, but has the advantage that its estimates can be directly compared to those from log-linear matching functions.

Column 1 in Table 2 presents estimates of a log-linear matching function, having excluded unemployment and vacancies beyond 10km, as the estimates in Table 1 suggest that their impact is negligible. Column 2 estimates the level version of this equation by non-linear least squares, excluding observations with zero vacancy outflow, thus on the same sample as in the first column. The estimates are qualitatively similar, with a considerable reduction in the size of the coefficients on all ratio variables. Column 3 estimates the levels model but includes the ‘zeroes’, i.e. the estimation method is the same as in column 2, but with a larger sample size. The estimates obtained are very close to those reported in column 2. Finally, columns 4 and 5 report results for the log-linear and linear models estimated for one month only (February 2005), which will feature in some of the estimates of Section 5.

The results of Tables 1 and 2 are consistent with a simple matching model with spatial spillovers. However, these specifications have limitations for making inference about the size of local labor markets, as they are not informative about the reasons for the spillovers. In other words, the estimated effect of the number of unemployed 10km away on the probability of filling vacancies in \( b \) may result from both those workers directly applying to vacancies in \( b \), and from them applying for vacancies local to them, which then become harder to obtain, and causing workers 5km away from \( b \) to shift their search efforts towards vacancies in \( b \). These two scenarios, while observationally equivalent in reduced-form estimates, have different implication for the size of local labor markets. To address this point the next Section proposes a more explicit model of job search across space.

### 4 The job search model

Our methodology relates job matches in an area to the number of applications received by vacancies within the area. The novel element consists in deriving job applications at each location from a job search model in which unemployed workers in one area may consider vacancies in every other area, according to the expected success rate of job applications at different locations and the utility enjoyed in a job in case of success. Such utility crucially depends on the distance to the job. The expected number of applicants for a job in an area represents a measure of both of the ease of filling vacancies in that area, and of job competition faced by workers applying for jobs there.

We next outline the model of job search across space, encompassing both the number of applications made and their spatial distribution, and we then relate applications to job
4.1 The application process

There are $U_a$ unemployed workers and $V_a$ vacancies in each area $a$ of the economy. Each worker decides which of the existing vacancies to apply for, and applications are simultaneous. Assume that an application to vacancy $i$ has a probability $p_i$ of being successful, and if so it generates utility $u_i$. Assume further that the probability of more than one application being successful is infinitesimal, so that expected returns from search for a worker can be written as:

$$\sum_i D_ip_iu_i,$$

where $D_i$ is a binary variable taking the value 1 if a worker applies to job $i$ and zero otherwise.

Workers have a cost function for $N$ applications of the form:

$$C(N) = \frac{c}{1+\eta}N^{1+\eta},$$

so that the net expected utility from job search can be expressed as:

$$\sum_i D_ip_iu_i - \frac{c}{1+\eta} \left( \sum_i D_i \right)^{1+\eta}.$$

A worker applies to a vacancy if the expected utility from doing so is higher or equal to the marginal cost $C'(N)$. This happens if

$$p_iu_i \geq c \left( \sum_i D_i \right)^{\eta} = cN^\eta.$$  

Workers apply to jobs in decreasing order of the associated expected utility, until expected utility falls below the marginal cost of an extra application. Whether a worker applies to a particular vacancy only depends on the expected utility provided and the marginal cost of an application, and other vacancies only affect this decision through the impact of the number of applications being made on the cost of the marginal application.\(^6\)

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\(^6\)The assumption that the probability of more than one application being successful is infinitesimal plays an important role here. If this assumption is not met then one cannot rank vacancies by their expected utility and the decision problem does not lead to such a simple rule. To see this more formally, suppose that we can order jobs in terms of utility, with job 1 offering a higher utility than job 2 and so on. Furthermore, assume that the jobs that offer a higher utility have a lower probability of success so that $p_1 < p_2 < \ldots$ (i.e. that dominated jobs are not applied for). In this case a worker only accepts job $i$ if no job applications to lower jobs have been successful. The expected utility from applying to a set of jobs is thus $\sum_i D_ip_iu_i \Pi_{j=1}^{i-1}(1-p_j)^{D_j}$. This leads to a decision rule in which the marginal benefit of applying to vacancy $i$ can be written as $p_i(u_i - E_i)(1 - Q_i)$, where $Q_i$ is the probability of getting a better job than $i$ and $E_i$ is the expected utility from jobs worse than $i$, conditional on a better job not being obtained. The effect of other applications on the decision to apply to vacancy $i$ is no longer limited to their effect on marginal costs. But the difference between this specification of marginal benefit and the one we use is small if $Q_i$ and $E_i$ are small. Chade and Smith (2006) provide a more complete analysis of optimal decision rules in this case.
In what follows we assume – as is standard in models of directed search – that success in a particular job application depends on the expected number of applications to that job, which we denote by $A$. Denote the probability of being the successful applicant by $p(A)$, with $p'(A) < 0$. The congestion effect that links the probability of success to the number of applicants will be captured by one of the key parameters in the model.

The parameter $\eta$ (or, more accurately, a transformation of it) is related to the returns to scale in the model. The issue of constant versus increasing returns to scale is a recurrent question in the matching literature, as increasing returns lead to the possibility of multiple equilibria (Diamond, 1982). If $\eta = 0$, there is a constant marginal cost of an application and an unemployed worker applies to a vacancy if the expected utility is above this marginal cost. In this case a doubling in the number of vacancies leads to a doubling in the number of applications each unemployed worker makes. The average number of applicants per vacancy remains unchanged, and so does the probability of filling each vacancy. The total number of matches then also doubles. In this situation there are constant returns to scale to vacancies alone. If one doubles both vacancies and the number of unemployed workers, then the number of applications will rise four-fold, as both the applications per worker and the number of workers double. This implies increasing returns to scale.

At the other extreme, consider $\eta = \infty$. This should be thought of as a case in which each unemployed worker has a fixed number of applications to make and will apply to those vacancies that offer the highest expected utility. In this case a doubling of vacancies and unemployment leads to a doubling of applications, as applications per worker are unchanged and the number of the unemployed has doubled. Hence applications per vacancy are unaltered, the probability of filling a vacancy is unaltered, and the total number of matches will double. This corresponds to the case of constant returns.

Our set-up makes it harder to rationalize the possibility of decreasing returns, for which we would have to introduce some extra form of congestion in the model. The estimates presented so far are very close to constant returns to scale for the economy as a whole. However, our model is consistent with decreasing returns to vacancies and unemployment in individual areas – typically doubling vacancies and unemployment in a particular area would result in a lower probability of filling jobs in that area due to spillovers across neighboring areas.

We further assume that the utility from a job in area $b$ for someone from area $a$ is given by

$$u_{ab} = f_{ab}\varepsilon,$$

where $f_{ab}$ represents the intrinsic attractiveness of a job in area $b$ for someone in area $a$ and $\varepsilon$ is an idiosyncratic component, which is assumed to have a Pareto distribution with exponent $k$. A natural specification for $f_{ab}$ is a function declining with the distance between $a$ and $b$, so that jobs in more distant areas are less attractive.
Hence, using (4), an individual in $a$ applies to a vacancy in $b$ if
\[ p(A_b) f_{ab} \geq c N_a^\eta, \]
where $N_a$ denotes the total number of applications made by each worker in $a$. Given the assumption that $\varepsilon$ has a Pareto distribution, this happens with probability
\[ \Pr (p(A_b) f_{ab} \geq c N_a^\eta) = \left( \frac{p(A_b) f_{ab}}{c N_a^\eta} \right)^k. \] (5)

Although there is some uncertainty about whether an individual applies to a particular vacancy, because of the idiosyncratic utility component, we apply the law of large numbers, so that the total number of applications can be treated as non-stochastic. The number of applications sent from unemployed workers in $a$ to vacancies in $b$ is thus given by:
\[ N_{ab} = V_b \left( \frac{p(A_b) f_{ab}}{c N_a^\eta} \right)^k. \] (6)
Summing the $N_{ab}$ terms across all possible destination areas $b$ yields:
\[ N_a = \sum_b V_b \left( \frac{p(A_b) f_{ab}}{c N_a^\eta} \right)^k, \]
which can be solved to obtain $N_a$:
\[ N_a = \left[ c^{-k} \sum_b V_b (p(A_b) f_{ab})^k \right]^{-\gamma}, \] (7)
where $\gamma = 1/(1 + \eta k)$. The case of a constant marginal cost of an application, $\eta = 0$, corresponds to $\gamma = 1$, while the case of a fixed number of applications, $\eta = \infty$, corresponds to $\gamma = 0$.

Combining (6) and (7), we solve for the total number of applications made by the unemployed in $a$ to vacancies in $b$ as
\[ N_{ab} = c^{-k \gamma} V_b (p(A_b) f_{ab})^k \left[ \sum_{b'} V_{b'} (p(A_{b'}) f_{ab'}) \right]^{-\gamma-1}. \] (8)

The intuition behind expression (8) is that the number of applications sent from area $a$ to area $b$ depends on job opportunities in area $b$ ($V_b$), how attainable they are ($p(A_b)$), and how far they are located from $a$ ($f_{ab}$). The term in square brackets can be interpreted as a weighted average of vacancies across the whole economy, where weights are given by a combination of their attainability and distance to $a$. This term captures the ‘effective’ size of the economy, and would simply work as a normalization in the case of constant returns ($\gamma = 0$).
The number of applications received by vacancies in $b$ is equal to all applications that unemployed workers decide to send to area $b$ from all areas $a$. Thus the ratio of applications per vacancy in $b$, denoted by $A_b$, is given by

$$A_b = \sum_a N_{ab} \frac{U_a}{V_b}$$

$$= c^{-k\gamma} \sum_a U_a \left( p(A_{ab}) f_{ab} \right)^k \left[ \sum_{b'} V_{b'} \left( p(A_{b'}) f_{ab'} \right) \right]^{\gamma-1}.$$  \quad (9)

Equation (9) states that the number of applications per job in area $b$ depends on the distribution of the unemployed across all possible origin areas $a$, how far they are located from $b$ ($f_{ab}$), and how attainable they perceive job vacancies in $b$ to be ($p(A_b)$).

In our baseline empirical specification we make two further functional form assumptions to estimate (9). First, we express $p(A_b) = A_b^{-\tilde{\beta}}$, where $\tilde{\beta} > 0$ denotes the effect of job competition on applications to jobs in a given area.\footnote{The functional form $p(A_b) = A_b^{-\tilde{\beta}}$ can be thought of as an iso-elastic approximation to the expression that would be derived from an urn-ball model describing how vacancies are filled. Denote by $\pi$ the probability that any particular candidate is acceptable for a given job vacancy. The probability that the vacancy is not filled is $(1-1)^{\lambda_k}$; the probability that the vacancy is filled is $1 - (1-1)^{\lambda_k}$; and the probability that any particular applicant is selected is $[1 - (1-1)^{\lambda_k}] / A_b$. We approximate this expression as $A_b^{-\tilde{\beta}}$. Both expressions are decreasing and convex in $A_b$, so we would be fitting similar functional forms to our data, but using the $A_b^{-\tilde{\beta}}$ approximation instead of the exact formula makes the model substantially more tractable.} Secondly, we express $f_{ab} = \exp(-\tilde{\delta} d_{ab})$, where $d_{ab}$ is the distance between $a$ and $b$, and $\tilde{\delta}$ measures the exponential rate of decay of the attractiveness of a given job with distance to that job. Distance can be measured, alternatively, as geographic distance, commuting time, or commuting cost. In the section on robustness we also estimate some more general specifications which express $f_{ab}$ as a function of worker composition in $a$, job composition in $b$, and commuting flows between $a$ and $b$. One may further assume that employers are less likely to select workers with longer commutes (for example if they are more likely to quit). In this case $p(.)$ would also depend on distance, but inspection of (9) shows that we cannot identify this separately from the cost of distance in the utility function. Hence our estimated cost of distance should be interpreted as encompassing all reasons why workers are less likely to match to more distant jobs.

Under these assumptions we can solve for $A_b$:

$$A_b = \left\{ c^{-k\gamma} \sum_a U_a \exp(-\tilde{\delta} d_{ab}) \left[ \sum_{b'} V_{b'} A_{a\tilde{\beta}}^{b'} \exp(-\tilde{\delta} d_{ab'}) \right]^{\gamma-1} \right\}^{1/(1+\beta)},$$  \quad (10)

where $\beta = k\tilde{\beta}$ and $\delta \equiv k\tilde{\delta}$.

Equation (10) is the key relationship delivered by our spatial job search model, and captures all the inter-dependencies between areas. In particular, the number of applicants to
jobs in b is likely to be influenced (even if only very slightly) by unemployment and vacancies in all other areas, because they are ultimately linked through a series of overlapping labor markets. This expression might be thought impossibly difficult to solve as, if we have 8,850 wards, it has 8,850 equations in 8,850 unknowns. But, under reasonable conditions, it can be shown that (10) is a contraction mapping, in which case it can be solved iteratively and economically to obtain $A_b$. This is the key feature that allows us to estimate a model with a number of areas that far exceeds those used in other similar applications, including the gravity models used in trade applications (see, for example, Eaton and Kortum, 2002).

To prove that (10) is a contraction mapping, we rewrite it in log form:

$$\ln A_b = \frac{1}{1 + \beta} \left\{ -k\gamma \ln c + \ln \sum_a U_a \exp(-\delta d_{ab}) + (\gamma - 1) \ln \left( \sum_{b'} V_{b'} e^{-\beta \ln A_{b'} \exp(-\delta d_{ab'})} \right) \right\}. \tag{11}$$

Expression (11) can be thought of as a mapping from one set of log applications across areas to a new set. Let’s denote this mapping by $T(\ln A)$. To apply Blackwell’s sufficient conditions for a contraction, consider $T(\ln A + z)$. Simple algebraic manipulation shows that

$$T(\ln A + z) = T(\ln A) + \frac{\beta(1 - \gamma)}{1 + \beta} z < T(\ln A) + z, \tag{12}$$

which meets the conditions for a contraction (see Stokey and Lucas, 1989, p. 54).

It is worth discussing why we can only identify $\beta = k\tilde{\beta}$ and $\delta = k\tilde{\delta}$, and not the underlying parameters $\hat{\beta}$ and $\hat{\delta}$. The reason is that an increase in the size of the idiosyncratic component of the utility from a job – measured by $k$ – is observationally equivalent to a change in the cost of distance or the effect of congestion on the probability of obtaining a job. If the idiosyncratic component is very small, then, for the same number of applicants, a worker is very likely to apply to a closer job than to a more distant one. In other words, this scenario has observable consequences that are equivalent to one with a higher cost of distance but a more important idiosyncratic component. Similarly for the effect of the number of applicants, holding distance to a job constant.\(^8\)

A useful result that can be obtained from (10) is that $A_b$ is homogeneous of degree $\gamma/(1 + \beta \gamma)$ in $U_a$ and $V_b$, and this relates to the returns to scale in the matching process. In particular, $\gamma = 0$ implies constant returns, while $\gamma/(1 + \beta \gamma) > 0$ implies increasing returns. This can be seen more clearly in the special case in which areas are isolated, such that $f_{ab} = f > 0$ for $a = b$, and $f_{ab} = 0$ for $a \neq b$. In this case the number of applications per

\(^8\)Finally, one might also notice that (10) also contains a ‘constant’, $c$. But, one can normalize this to one without loss of generality as the number of applications per vacancy is not actually observed in our data, but just a theoretical construct. This also means that it makes no sense to actually discuss the computed number of applications per vacancy as a guide to whether the model is ‘plausible’ or not. What is observed is the actual number of matches that we posit to be related to the number of applications per vacancy.
vacancy in an area can be written as a function of the U-V ratio in the area and of the absolute number of vacancies:

\[
\ln A_b = -\frac{k\gamma \ln c}{1 + \beta} + \frac{1}{1 + \beta \gamma} \ln \left(\frac{U_b}{V_b}\right) + \frac{\gamma}{1 + \beta \gamma} \left[\ln (V_b) + \ln(f)\right].
\] (13)

As the vacancy outflow rate in an area depends on the number of applications per job in that area, expression (13) implies a relationship between the vacancy outflow rate, the local U-V ratio, and the number of vacancies, which is very similar to the log-linear specification usually estimated in the matching function literature (see Petrongolo and Pissarides, 2001). When \(\gamma = 0\) the number of applications per job only responds to the U-V ratio, and is independent of the size of the labor market, represented by \(V_b\), implying constant returns.

To summarize, our model has three key parameters:

- \(\delta\), the cost of distance;
- \(\beta\), the congestion effect, that measures how strongly workers are deterred from applying to jobs in areas where they expect a large number of applications;
- \(\gamma\), related to the returns to scale in the matching function.

### 4.2 From applications to job matches

The vacancy outflow in an area is used as a proxy for job matches, and the vacancy outflow rate is expressed as a function of the expected number of applications per job vacancy, i.e.

\[
E\left(\frac{M_b}{V_b}\right) = \Psi(A_b), \quad \Psi'(\cdot) > 0.
\] (14)

Various functional forms have been used in the literature for estimating \(\Psi\), based on possible microfoundations of the matching function and empirical tractability. The simplest microfoundation for a matching function like (14) is an urn-ball model,\(^9\) in which firms play the role of urns and applications the role of balls. Because of a coordination failure, a random placing of the balls in the urns implies that some urns will end up with more than one ball and some with none. Thus an uncoordinated application process will lead to overcrowding in some jobs and no applications in others.

Conditional on receiving an application, a vacancy may still remain unfilled if one allows for worker heterogeneity and thus the possibility that the applicant may not be suitable for the job. The probability that a given job applicant is selected for a job is \(A_b^{-\beta}\). Thus the probability that a given vacancy is not filled by any applicant is \((1 - A_b^{-\beta})A_b\), and the vacancy

---

\(^9\)See Butters (1977) and Pissarides (1979) for early microfoundations of the matching function based on an urn-ball model.
outflow rate is $M_b/V_b = 1 - (1 - A_b^{-\beta})^{A_b}$. For small enough $A_b^{-\beta}$, $(1 - A_b^{-\beta})^{A_b} \simeq \exp(-A_b^{1-\beta})$, and thus we estimate

$$\frac{M_b}{V_b} = 1 - \exp\left[ -\exp(\alpha)A_b^{1-\beta} \right] + e_b,$$

(15)

where we have added a non-negative multiplicative constant $\exp(\alpha)$ and an error term $e_b$. The term $\exp(\alpha)A_b^{1-\beta}$ represents the hazard at which vacancies are filled. Alternatively, a simple log-linear specification can be estimated, i.e.

$$\frac{M_b}{V_b} = \exp(\alpha)A_b^{1-\beta} + e_b.$$  

(16)

The nice feature of the urn-ball specification (15) is that it ensures a vacancy outflow rate between 0 and 1, while this is not imposed by the log linear specification (16). However, (16) has the advantage that it yields a constant elasticity of the vacancy outflow with respect to the number of jobseekers and vacancies, and this property allows us to more easily assess the returns to scale in matching. As we note below, both specifications yield virtually identical results. Whether estimating (15) or (16), $A_b$ is implicitly defined by (10), and thus $\delta, \beta, \gamma$ are further parameters to be estimated. We estimate (15) and (16) by maximum likelihood, and at every iteration of the maximization solve the contraction mapping in (10).\(^{10}\)

It is helpful to highlight the relationship between our model of job search, in which vacancies receive a number of applications and then, possibly, choose one of them, and the more common modelling strategy based on a flow arrival rate of job applicants, in which the first acceptable candidate is chosen (e.g. Pissarides, 2000). In our modelling strategy one could reinterpret the number of applications as a decision about the rate at which to apply for jobs, combined with a decision about the distribution of these applications over vacancies in different areas. This mechanism would also lead to a specification relating the vacancy outflow rate to the number of ‘applicants’, in which the number of applicants is re-interpreted as the rate at which job applicants apply to the firm.

Our approach has also similarities to the way in which markets for differentiated goods are represented in Industrial Organization models. One can think of a ‘product’ as being a job in a particular area. Compared to most IO applications we have a very large number of ‘products’, and a priori information on which of these products are the closest substitutes – those closer in space – which allows us to reduce the dimensionality of product heterogeneity. Consumers are also differentiated – in our application they are differentiated by space, the same differentiation as the products. One can think of information on unemployment and vacancies as being information on demand by different types of consumers and supply of different products. Our variable ‘applications per vacancy’ functions like a price in the sense that more applications discourage consumers from purchasing a product of a particular type.

\(^{10}\)To avoid dropping observations with zero outflows, both (15) and (16) are estimated in levels instead of logs.
and encourage them to divert their demand to other products. Our outcome variable, the number of matches, can be thought of as representing the market outcome in a quantity space. The equation we estimate is essentially a reduced-form equation for the quantity traded as a function of the demand and supply fundamentals. One can retrieve the estimates of the demand functions under the assumption of exogenously fixed supply of vacancies.

5 Results

5.1 Main estimates

Our first set of results is based on an urn-ball specification of the matching function, as shown in equation (15). For reasons of computing capacity, we cannot estimate our regression equation on the whole sample period, and we thus estimate it separately for each month from May 2004-April 2006. This, however, has the advantage that each month’s estimate can be thought of as a draw from the data (not necessarily independent, and we can check for serial correlation in the estimates), thus giving us an idea of the standard error on our estimates from their variation across different months, which we can then compare with the standard error produced by our structural estimation method.

Table 3 reports time averages of the parameters of interest, together with their standard deviations, minimum and maximum values. Distance of workers to jobs is measured as geographic distance, and thus \( \delta \) represents the exponential rate of decay of a job’s attractiveness with distance in km to that job. An average \( \delta \) of 0.3 is consistent with relatively fast decay of job utility with distance. To see this, consider two random jobs, one from the workers’ residential ward and the other at a distance \( \delta \), which receive the same number of applications. If \( \varepsilon \) denotes the idiosyncratic component of utility for the local job and \( \varepsilon_1 \) for the more distant job, the more distant job would be preferred if \( e^{-\delta \delta} \varepsilon_1 > \varepsilon \). Under the assumption that \( \varepsilon \) and \( \varepsilon_1 \) are Pareto distributed, simple algebra shows that the more distant job is preferred with probability \( \frac{1}{2} e^{-\delta \delta} \). With \( \delta = 0.3 \), this implies that a worker would prefer the local job over one that is 5km distant in 89% of cases, and over one that is 10km distant in 95% of cases.

The congestion parameter \( \beta \) is positive, implying that the probability of being selected for a given job opening falls with the number of applicants, with an average elasticity of about 0.75. The average estimate for \( \gamma \) is negative, implying decreasing returns in matching, although the low point estimate again suggests a scenario very close to constant returns. Overall, both \( \delta \) and \( \beta \) appear to be precisely estimated over the sample period, but there is slightly more variation in \( \gamma \). If one is willing to make the hypothesis that the month-to-month variation in the relevant variables is largely driven by independent, random shocks, then the average parameter estimates and associated standard deviations can be used for bootstrap inference. Thus one can conclude that while both \( \delta \) and \( \beta \) are highly statistically
significant, γ is not statistically different from zero. In Figure A2 of the Appendix we plot point estimates of these parameters over the 24 months in our sample. The series fluctuate moderately over the sample period, and show no definite trend, and we could detect no significant serial correlation of either first or second order in δ, β or γ.

In Table 4 we report estimates of alternative specifications of the job application model for February 2005, and Table A2 of the Appendix reports the corresponding estimates for the whole sample period, obtained again as averages of monthly estimates for May 2004-April 2006. The simple criteria used for picking a reference month in Table 4 is that it should not be December or a summer month, and that the parameter estimates for this month should be quite close to the sample averages to make the estimates of Table 4 well representative for the whole sample period. Below we will not comment the average estimates of Table A2 separately, because indeed they are very close to those reported in Table 4, both in terms of parameter estimates and their standard errors.

Column 1 in Table 4 estimates the basic specification of an urn-ball matching function, with the attractiveness of jobs represented by geographic distance to the worker’s location. The associated standard errors are corrected for some (arbitrary) structure of spatially correlated shocks. Both β and δ are highly statistically significant, while γ is not statistically different from zero. To determine the returns to scale in the matching function, recall that \( \beta = \frac{1 + \gamma}{1 + \beta \gamma} \) in \( U \) and \( V \). Thus the returns to scale can be obtained multiplying by \( \gamma/(1 + \beta \gamma) \) the elasticity of matches with respect to applications. Such elasticity is equal to \( (1 - M_b/V_b)/(-\exp(-\beta \gamma \mu)) \), and can be computed using estimates of \( \alpha \) and \( \beta \), and predicted values for \( M_b/V_b \) and \( A_b \). The sample average of this expression equals -0.011, implying a returns-to-scale estimate of 0.989, which is very close to constant returns.

Column 2 assesses whether job applications are a sufficient statistic for describing local job matches. In other words we test whether local unemployment still retains some explanatory power on local job matches, once one controls for applications per job as predicted by the model. For this purpose we estimate the following urn-ball matching function:

\[
\frac{M_b}{V_b} = 1 - \exp\left[-\exp(\alpha)A_b^{1-\beta} \left( \frac{U_b}{V_b} \right)^{\alpha_1}\right] + e_b, \tag{17}
\]

where \( A_b \) is obtained from the contraction mapping (10) and the local unemployment to vacancy ratio is included as an extra regressor in the matching equation. Column 2 shows that the main parameter estimates δ, β and γ stay virtually unchanged from the specification of

\[11\]In particular, we assume that spatial correlation across wards decays at rate δ with ward distance or commuting cost. Our estimated variance-covariance matrix of the parameters is given by \( \hat{V} = \hat{\sigma}^2(\hat{X}'\hat{X})^{-1}(\hat{X}'\hat{\Omega}\hat{X})(\hat{X}'\hat{X})^{-1} \), where \( \hat{\sigma}^2 \) is the sum of squared residuals divided by the number of observations, \( \hat{X} \) is the matrix of partial derivatives of the regression function with respect to right-hand side variables, and the spatial correlation matrix \( \hat{\Omega} \) is proxied by \( \exp(-\hat{\delta}D) \), where \( D \) is given by the distance matrix, and \( \hat{\delta} \) is the associated parameter estimate.
column 1, and that the local unemployment to vacancy ratio has a small, though statistically significant, impact on the matching rate. Although the coefficient on the unemployment to vacancy ratio is much lower than the coefficient on applications, given by \(1 - \beta = 0.207\), this finding would point at a failure of our job application model, namely there are some local effects in matching that a simple job application model across space fails to capture.

Similarly as we noted for the log linear matching functions estimated in Section 3, there may be a problem of division bias here if the vacancy stock is measured with some error, as it appears at the denominator of both the dependent variable and of one of the right-hand side variables. A simple way to address the division bias problem in this context (analogous to a ‘control function’ approach) consists in including the vacancy stock among right-hand side variables, with exponent \(\alpha_2\). This reveals whether the positive estimated impact of \(U_b/V_b\) in column 2 stems from its numerator or denominator. Column 3 shows that the impact of the \(U_b/V_b\) ratio on the vacancy outflow rate is somewhat reduced, and becomes insignificantly different from zero, when one controls for the total vacancy stock.

In column 4 we estimate a similar specification to that of column 1, having expressed the job matching rate as a log-linear function of applications per job, as in equations (16). While estimates are very similar to those obtained on an urn-ball matching function, the log-linear specification has the advantage of delivering a constant elasticity of the matching rate with respect to applications, equal to \(1 - \beta\). As \(A_b\) is homogeneous of degree \(\gamma/(1 + \beta\gamma)\) in \(U\) and \(V\), this implies an elasticity of the matching rate with respect to \(U\) and \(V\) equal to \((1 - \beta)\gamma/(1 + \beta\gamma)\). Using estimates from column 4, this is equal to \(-0.008\). A Wald test on this statistics gives a \(\chi^2\) value of 0.193, which falls below the 5% critical value of 3.84, thus the hypothesis of constant returns to scale cannot be rejected.

### 5.2 Robustness analysis

This section explores the robustness of our main estimates to a number of extensions. Specifically, we (i) consider alternative concepts of distance, (ii) control for occupational mismatch and commuting flows between areas as further determinants of the attractiveness of jobs at various locations, and (iii) discuss the interpretation of our estimates in an extension in which wages are endogenously set by employers in order to attract job applicants.

In column 5 of Table 4 we estimate an urn-ball matching function, having modelled the utility of jobs at different locations as a function of commuting times, expressed in one-way commuting minutes. The results are fairly similar to those based on geographic distance, with the job congestion estimate at 0.75, and again close to constant returns to scale. The estimate for the \(\delta\) parameter of course differs from the one in column 1, being based on a different distance metrics. The new \(\delta\) estimate means that, all else equal, a worker chooses

\[\text{The data on commuting costs were obtained from Daniel Graham at Imperial College and have their origins in transport planning.}\]
to apply to a local job rather than to a job 5 minutes away in 82% of cases. In column 6, distance is measured by one-way commuting costs, and the corresponding δ estimate implies that a worker chooses to apply to a local job rather than to a job 1£ away in 77% of cases (at 2001 prices).

All three measures of distance – geographic distance, commuting time and commuting costs – imply a very high decay of the probability of applying to a given job with distance. While these estimates are obtained on a relatively unskilled sample, for which the labor market may be more local than for the universe of jobseekers, the estimates of Bonhomme and Jolivet (2009) are suggestive of very high distance costs on a sample that is representative of the overall population. Using information on job satisfaction from the ECHPS, they find that workers in Europe are typically willing to forgo large fractions of their salaries to become satisfied with their commuting distances/costs, ranging from 40% in France to 14% in Austria. Unfortunately, they do not report estimates for the UK.

We also consider that target labor markets may differ not only in terms of geographic distance (or commuting costs) from an applicant’s location, but also in terms of the skill composition of available jobs, as measured by occupations. Indeed failure to recognize job and worker heterogeneity along dimensions other than distance would induce us to overstate the cost of distance. For example, if very few workers in a apply to jobs in b, our model would interpret that a and b are located too far apart to belong to the same local labor market, but in reality it may be that workers in a simply do not have the skills to perform jobs in b. To control for worker and job heterogeneity, we construct an index of mismatch between the skill composition of each origin labor market and that of each destination labor market, based on the occupational composition of claimants and job vacancies.\textsuperscript{13} In particular, we extract data on claimants and job vacancies by CAS ward and 1-digit occupation, and construct the following index of occupation dissimilarity between origin area a and destination area b:

\[ m_{ab} = \sum_{h=1}^{8} \left| \frac{U_{ha}}{V_a} - \frac{V_{hb}}{V_b} \right|, \]  

(18)

where the occupation categories considered are: (1) managers and professionals; (2) associate professionals and technical occupations; (3) administrative and secretarial occupations; (4) skilled trades occupations; (5) personal service occupations; (6) sales and customer service occupations; (7) process, plant and machine operatives; (8) elementary occupations. We then express the utility of a job in area b for an unemployed in area a as a function of both the geographic distance and the occupational mismatch index in (18):

\[ f_{ab} = \exp(-\tilde{\delta}d_{ab} - \mu m_{ab}), \]

where μ is an extra parameter to be identified. The results are reported in column 7, where the estimate for μ is positive and significant, implying that the unemployed are discouraged

\textsuperscript{13}For the unemployed the occupation refers to the type of job sought.
from sending applications to areas where the array of jobs available would not match their sought occupation. Quantitatively though, the impact of occupational mismatch on job applications is relatively modest. The mismatch index obtained has an average of 1.067, with a standard deviation of 0.042. Thus a one standard deviation increase in the mismatch index would imply a fall in the utility of applying to a given area by 3.2%, while a one standard deviation increase in distance would imply a fall in such utility by 98.7%. Most importantly, our estimate for the cost of distance is clearly robust to the inclusion of a local mismatch index.

We finally explore the role of social networks among neighbors in our job search framework. The idea that social networks are important in labor markets has received increasing attention (see Calvo-Armengol and Jackson, 2004a, 2004b, among others). Workers may obtain information about available jobs from their social contacts, and if a good source of contacts is one’s neighbors, the outcome of these networks are clusters of commuters from one area to another. The empirical studies by Topa (2001), Bayer, Ross and Topa (2008) and Hellerstein, McInerney and Neumark (2011) contain evidence on the importance of residence-based networks. Topa (2001) estimates a model of social interactions in neighborhoods and relates its predictions to the observed spatial correlation in unemployment rates. Bayer et al. (2008) show that workers who live on the same block are also significantly more likely to work in the same block. Hellerstein et al. (2011) use matched employer-employee data to show that coworkers are significantly more likely to live in the same census tract than those who work in the same census tract but in different firms.

We investigate the social network hypothesis exploiting data on commuting flows between every two wards, obtained from the Special Workforce Statistics of the 2001 Census. We think of these commuting flows as linkages between wards that existed prior to our sample period. If networks are important we expect that, conditional on distance, workers are more likely to apply to jobs in wards towards which there is a large commuting flow from their own ward. To capture this idea, commuting flows enter the utility of a job in \( b \) for a worker in \( a \), i.e.

\[
 f_{ab} = \exp(-\delta d_{ab} + \zeta comm_{ab}),
\]

where \( comm_{ab} \) denotes the number of individuals resident in \( a \) who commute to \( b \). The commuting flow \( comm_{ab} \) is endogenous to distance, but the likely bias on \( \zeta \) in case of measurement error in distance is positive. For example, if two wards are linked by a fast bus service, this would lead to large commuting flows, given the (mis)measured geographic distance. The results are reported in column 8 of Table 4. Commuting flows have a negative, rather than positive, impact on the attractiveness of jobs at various locations.\(^{14}\) Overall, we find no evidence of the expected impact of residence-based networks in our estimates, and

\(^{14}\)When measuring distance using either commuting time or commuting costs, the coefficient on commuters falls in both absolute size and significance, but it remains firmly negative (results not reported).
the negative coefficient on commuting flows seems instead consistent with a congestion effect along workers’ commutes.

While we are only taking into account horizontal heterogeneity between workers and jobs, represented by distance (or occupational mismatch), this model could be generalized to allow for some form of vertical heterogeneity between jobs at different locations. For example, workers at all locations positively value the wage attached to a job offer, and thus, other things equal, receive higher utility from applying to jobs in high-wage areas than to jobs in low-wage areas. In this case one could have \( f_{ab} = \exp(-\tilde{d}_{ab})W_b^{\phi_2} \), in which \( W_b \) denotes destination-specific wages, and \( \phi \) is the associated effect on utility. Unfortunately, there is no wage data available for the UK at the ward level because the Census has never collected wage information.

But even if we had measures of ward-level wages that we could include in our estimation we would need to address the problem that wages are endogenously chosen by employers in response to the difficulty in recruiting workers, something that our model aims to explain. Suppose that employers choose wages to maximize the expected profits from a vacancy so that the level of wages \( W \) is chosen to maximize \( (P - W)\Psi(A(W)) \), where \( P \) is the marginal revenue product of labor, the probability of filling a vacancy \( \Psi(\cdot) \) is defined by (14), and we allow the number of applicants to depend on the offered wage. The first-order condition for this maximization problem can be written as:

\[
W = P \frac{\epsilon_{\Psi A}(A)\epsilon_{AW}}{1 + \epsilon_{\Psi A}(A)\epsilon_{AW}}
\]

where \( \epsilon_{\Psi A}(A) \) is the elasticity of \( \Psi \) with respect to \( A \) and \( \epsilon_{AW} \) is the elasticity of \( A \) with respect to \( W \). As \( \Psi \in [0, 1] \), and most vacancies are filled, it is likely that \( \epsilon_{\Psi A}(A) \) is decreasing in \( A \), so the first-order condition (19) implies that wages and applicants are negatively correlated in equilibrium. Intuitively, firms that receive few applications and find it hard to recruit try to mitigate their disadvantage by offering higher wages, but do not manage to completely overcome it. If we represent this outcome by \( W_b = W A_b^{-\phi_2} \), where \( W \) is a constant, we have \( f_{ab} = \exp(-\tilde{d}_{ab})W^\phi A_b^{-\phi_2} \). Substituting this into (9), our empirical specification remains exactly the same except that the estimate for the exponent on \( A_b \) has to be reinterpreted as an estimate of \( (\beta + \phi_2) \). Effectively a high level of expected applicants discourage applications not just because job competition is stronger, but also because the employer would offer lower wages. The relevant conclusion is that all other parameters of the model, including the cost of distance, are unaffected by the endogeneity of wages.

To conclude, we compare the relative merits of the job application model with the conventional matching function in vacancies and unemployment in the specification of column 9, which only includes \( U_b/V_b \) as a regressor. The coefficient on \( U_b/V_b \) is positive and significant, but the adjusted \( R^2 \) is substantially lower than in the job application model of column 1.
Thus the job application model seems to perform better at explaining the variation in job matching rates than the simple matching function in unemployment and vacancies only.

5.3 Predicted commuting flows

Our estimated model has predictions for commuting patterns between any two wards. Specifically, the share of applications to ward $b$ that come from ward $a$ is given by the number of applications that the unemployed in $a$ send to jobs in $b$, divided by the total number of applications received by jobs in $b$, i.e.

$$\frac{U_a N_{ab}}{A_b V_b}. \quad (20)$$

As firms are assumed to select workers randomly within the pool of applicants, the ratio in (20) also denotes the proportion of total matches in ward $b$ that involve workers from ward $a$. Thus the number of vacancies in $b$ that are filled by workers in $a$ is given by

$$\frac{U_a N_{ab}}{A_b V_b} M_b. \quad (21)$$

The distribution of predicted commutes can be obtained as the share of workers who live in $a$ and work in $b$, for all possible pairs $(a, b)$. Given (21), this is equal to

$$\frac{N_{ab} M_b / A_b V_b}{\sum_{b'} N_{ab'} M_{b'}/ A_{b'} V_{b'}}. \quad (22)$$

These predictions are compared to Census data on commuting used in the previous section. The concepts of predicted and actual commuting may not coincide if workers who accept a job in a ward tend to relocate, for example to shorten their commute, or if jobseekers filling Jobcentre vacancies have different commuting patterns from jobseekers who find jobs via other methods.

However, external evidence on commuting behavior from the UK Labor Force Survey (LFS) shows that this is not a major concern. The LFS contains information on commuting times for those in new jobs and those in continuing jobs and, for those in new jobs, on how they obtained the job. Table A3 of the Appendix presents evidence on the average length of commute for these groups. The average commute for the category of workers we model – those who have recently got a job through a Jobcentre – is the same as for the overall employed population. As the characteristics of workers in different cells may differ, and they may be related to commuting times, we also compare differences in commuting times controlling for the method used to find the current job, age, gender, region and year (results not reported), and we find no significant difference between commuting times of those who found jobs via Jobcentres and those who are not on new jobs. This justifies comparisons between the commutes predicted by our model with the commuting data for the whole population.
Estimates from the baseline model of column 1 in Table 4 deliver a correlation between actual and predicted commuting flows – as implied by (22) – of 0.71. This is the pairwise correlation between two matrices of commuting flows (actual and predicted) which include several zeros, thus one may worry that a relatively high correlation between the two could be driven by the vast proportion of cells in either matrix with zero commuters. But when we restrict to cells with nonzero commutes we still obtain a correlation of 0.69. Interestingly, the correlation between actual and predicted commutes rises to 0.83 if one excludes ‘locals’ from the sample, i.e. individuals who live and work in the same ward (and this stays unchanged if we further exclude empty cells). Thus our model provides a fairly good representation of commuting patterns, but it reproduces the behavior of those who live and work in the same ward less accurately than that of commuters. This can be seen more clearly comparing the distributions of actual and predicted commutes, as shows in Table 5. Both distributions are hump-shaped, with a peak in the (0,5] km range, but the model tends to underpredict locals and as a consequence it overpredicts short-distance commutes. In particular, the model predicts that about 10% of individuals live and work in the same area, while in reality this proportion is about 24%. This is consistent with the finding that the local unemployment to vacancy ratio still plays a modest role in explaining variations in matching rates, having controlled for applications per job. Another possible interpretation is that the commuting data cover a number of self-employed individuals who may work from home, while the self-employed are not encompassed by our model.

6 Evaluating Place-Based Policies

There is a large and growing literature on the evaluation of place-based policies, increasingly using modern evaluation methods and better research designs (see Glaeser and Gottlieb, 2008, and Moretti, 2011, for recent surveys, and Kline and Moretti, 2013, for a model of place-based policies with frictional unemployment). This section assesses our model’s contribution in light of existing studies. This literature has to date not reached a clear consensus. One of the reasons may be that place-based policies vary greatly in both the size of the intervention and its nature. A typical place-based policy is a combination of various interventions, making it hard to identify which elements are or are not effective. Our model complements existing evaluations by illustrating consequences of isolated forms of intervention. Specifically, this section shows our model’s predictions following three common types of place-based policies: (i) an increase in vacancies in targeted areas (possibly induced by subsidies to job creation in those areas); (ii) an increase in the attractiveness of applicants from targeted areas (possibly...
induced by subsidies to the employment of residents of targeted areas or assistance with job search); (iii) an improvement in the transport infrastructure of targeted areas designed to make them more accessible.

We should be clear from the outset that our model, with its assumption of given vacancies and unemployment, cannot be used to answer the very important question of the extent to which place-based policies lead to vacancy creation in targeted areas or displace vacancies in neighboring areas or alter the residential decisions of workers (see Beaudry, Green and Sand, 2012, or Rupert and Wasmer, 2012, for recent attempts to combine search and residential mobility).

6.1 Local Labor Demand Stimulus

A key policy question for addressing spatial inequalities is whether unemployment may be alleviated in a depressed area using local stimulus to labor demand, or whether local stimulus is diluted across space through a chain reaction of local spillovers. To answer this question we introduce a labor demand shock in a given location, and use model predictions to simulate its effect locally and its decay with distance from the target location.

As an example, we consider an increase in the number of job openings in Stratford in East London, which was the main venue of the 2012 Olympic Games. This example combines a large increase in labor demand as a result of Olympic-related projects with a relatively depressed local labor market.16 Specifically, we simulate the impact of a doubling in the number of vacancies in Stratford and New Town Ward in a given month, from 464 to 928, under the assumption of constant returns to scale, i.e. imposing $\gamma = 0$, an assumption that is not rejected in our estimates. Under constant returns, the total number of applications made by workers at all locations is independent of the size of the economy, and thus is unaffected by the shock considered (see equation (7)). Values used for $\delta$ and $\beta$ are those reported in column 1 of Table 4. Based on these estimates, the model predicts a total increase in the vacancy outflow, and thus in the unemployment outflow, of 212.

The spatial diffusion of this shock is illustrated in Table 6, showing the predicted percentage change in applications per job (equation (10)), in the vacancy outflow (equation (15)), and the unemployment outflow (equation (21)), within alternative distance cutoffs from Stratford. As total applications in the economy are unchanged, applications per job on average fall. In Stratford, where vacancies double, applications per job fall by about 2.2%. Around Stratford, applications per job also fall, as Stratford attracts job applications from surrounding areas. This spillover effect decays with distance, and the percentage change in applications per job is below 1% beyond 10 km from Stratford, and virtually zero beyond 35 km. The number of vacancies filled in Stratford rises by 98.9%, with a very slight decline in

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16In February 2005, Stratford had a ratio of claimant unemployment to resident population of 6%, which was nearly three times higher than the average for England and Wales.
the probability of filling any one vacancy, given that the number of vacancies has doubled. There is a very tiny decrease in the number of vacancies filled in surrounding areas as well, because of increased competition for applicants in and around Stratford, but again this effect is virtually negligible.

Moving on to the change in the unemployment outflow, we find no evidence of any sharp local effect, with the unemployment outflow in Stratford only rising by 0.4%. If anything, the unemployment outflow within 20 km rises slightly more than in Stratford,\(^\text{17}\) and beyond this cutoff distance the change in the unemployment outflow becomes negligible. Spatial diffusion of this shock is shown graphically in Figure 1, in which wards around Stratford are shaded according to the average percentage change in the unemployment outflow. As the impact on vacancy and unemployment outflows is very modest we would also expect this policy to have limited effects on vacancy creation and residential mobility. While the location of vacancies and the unemployed is exogenous in our model, these predictions imply that incentives to relocate following local stimulus are small.

The bottom line is that, while labor markets are quite ‘local’, in the sense that the attractiveness of job offers strongly declines with distance, local labor markets do overlap; thus the ripple effect generated by local shocks implies that their propagation is fairly wide. One should therefore conclude that even strong local stimulus has a limited effect on the local outflow rate from unemployment, because a series of spatial spillovers dissipates a local shock across space. Specifically, unemployed workers living relatively close to Stratford divert some of their job search effort from their local wards towards Stratford. This reduces job competition in their local wards and attracts applications from elsewhere, and so on. This mechanism explains the spatial propagation of local shocks in the presence of relatively high costs of distance. As a corollary, one can imagine that a local employment stimulus is likely to have sizeable effects on local unemployment if there is a ‘firebreak’ across which few workers commute, as the firebreak prevents local stimulus to dissipate via the ripple effect. An important consequence is that stimuli in more isolated areas are expected to have larger local effects.

We next compare this prediction to actual data on job postings and the unemployment outflow around Stratford in the run-up to the 2012 Olympics. Much of the increase in labor demand took place in summer 2012 with running the Olympics itself, while some has built up steadily over time (e.g. in construction and retail). Panel A in Figure 2 presents time series for new vacancies advertised in Stratford, in wards within 3km of Stratford, and in London, all normalized to their January 2009 values.\(^\text{18}\) There is a steady increase

\(^{17}\)This non-monotonicity comes from the fact that the \(\sum_{\nu} V_{\nu} A_{\nu}^{-\beta} \exp(-\delta d_{\alpha\nu}) \)^{\gamma-1} term, capturing the extent of job competition, falls more in Stratford than elsewhere. This term determines the number of applications sent from each area \(\alpha\) to each area \(\beta\), according to (8), and thus the unemployment outflow in each area \(\alpha\), according to (21).

\(^{18}\)While information on the stock of vacancies in the NOMIS is not comparable before and after May 2006
in job openings in Stratford since the early months of 2011, with a peak in summer 2011, associated with the opening of a new shopping centre next to the London Olympic Park, and another even larger peak in spring 2012 in anticipation of the Games, with vacancy inflows running at about ten times the usual level. Other areas show no such trend. Panel B plots series for the unemployment outflow in the same areas as in Panel A, and shows little or no evidence of an increase in outflows in Stratford or surrounding areas as a result of the spike in vacancies. While this simple exercise does not aim to provide an exhaustive analysis of the local employment effects of the 2012 Olympics, the early indications are exactly in line with the predictions of our model and are consistent with negligible local effects of targeted labor demand stimulus, as shown in Table 6.

Several of the existing evaluations of place-based policies do not have the necessary information to determine the extent to which employment gains of local employment stimulus are concentrated on local residents or more diffused across space, either because information on the residential location of workers is unavailable or because units of analysis is fairly large (e.g. the counties in Greenstone and Moretti, 2004; Greenstone, Hornbeck and Moretti, 2010). However, results reported by Busso, Gregory and Kline (2012) for the US and Gobillon, Magnac and Selod (2010) for France suggest that it is local residents who benefit the most. However, in each case the policy being evaluated included both incentives to business to locate in the targeted areas and subsidies for hiring local residents. It may be the case that subsidizing employment of locals is the most effective element of intervention, and we consider such policy next.

### 6.2 Subsidizing Employment of Local Residents

Employment outcomes for workers in disadvantaged areas may be encouraged by combining local stimulus with subsidies for hiring residents in the targeted areas, or with assistance with job search. We model the policy target towards residents by assuming that the policy makes it more likely, other things equal, that residents succeed in the competition for jobs. We thus combine a doubling in vacancies in Stratford (as in Section 6.1) with an increase in the utility of Stratford jobs for all residents within 5 km, which is in turn equivalent to a reduction in their effective distance to Stratford, i.e.:

\[
\begin{align*}
    f_{ab} &= \exp(-\delta d_{ab}) + s \quad \text{if } d_{ab} \leq 5 \\
    f_{ab} &= \exp(-\delta d_{ab}) \quad \text{if } d_{ab} > 5,
\end{align*}
\]

(see footnote 3), the procedure for registering the inflow of newly advertised vacancies (reported in Figure 3) remains unchanged.

19This is Westfield Stratford City, opened on 13 September 2012 to become one of the largest urban shopping centres in Europe, with the creation of up to 10,000 permanent jobs.
where \( b \) denotes Stratford. In the simulation we pick \( s = 0.002 \), corresponding to a very modest increase in the utility for nearby residents to apply to jobs in Stratford.\(^{20}\) The results of this exercise are reported in Table 7, which is identical in structure to Table 6, and reports changes in job applications, job matches and the unemployment outflow at various distances from Stratford. The most important, and striking, consequence of introducing hiring targets is the substantial increase in the local unemployment outflow. Even a very mild hiring target is sufficient to double the unemployment outflow in the target area, while areas beyond 5 km are only modestly affected. This result is represented graphically in Figure 5, in which the dark area represents the set of targeted wards, with increases in the unemployment outflow in excess of 95%, while the next belt around this experiences increases in the unemployment outflow between 1% and 8%. While ripple effects are strong enough to dilute the effect of local stimulus across surrounding areas, local hiring targets are more effective in raising the local exit rate from unemployment, as they impose a discontinuity in the ripple effect to the advantage of those living inside the targeted area.

The intervention considered here is more ‘people-based’ than ‘place-based’ and suggests that one can benefit residents of targeted areas by increasing their effectiveness in the competition for jobs. Our model also suggests that ‘people-based’ policies that move individual’s residential location, but not into a completely new labor market, have little effect on employment outcomes. One of the best-known policies of this type is the Moving to Opportunities program, which offered low-income families housing vouchers to be used in low-poverty areas, and Katz, Kling and Liebman (2001) found no evidence of labor market effects of such program. Another similar example is the Toronto Housing program, which is also found to have negligible labor market effects (Oreopoulos, 2003).

### 6.3 Reduction in Transportation Costs

We finally assess the importance of transportation costs by simulating the impact of a sizeable reduction in the cost of distance between Stratford and central London, and in order to focus on distance costs alone we leave labor demand in Stratford unchanged. The idea is to evaluate the impact of an improved transport link between a high-unemployment area and the city centre, with relatively higher supply of jobs. Specifically, we simulate the effect of a faster connection between Stratford and Kings Cross Station in central London, by halving the distance between the two corresponding wards. Stratford and Kings Cross are located 8.4 km apart, and we build a new distance matrix in which the distance between the two wards is set at 4.2 km. We also re-calculate the distance between any two other wards \( a \) and \( b \) if either the distance \( a—Kings\ Cross—Stratford—b \) or \( a—Stratford—Kings\ Cross—b \) is shorter than the original distance \( ab \). This is equivalent to introducing a fast, non-stop service.

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\(^{20}\)The estimates of column 1 in Table 4 imply an increase in such utility of 0.7% for people living at the border of the target area (i.e. exactly 5 km from Stratford), and of 0.02% for those living in Stratford itself.
between Stratford and Kings Cross, allowing individuals near either node to re-optimize their travel schedule accordingly. As a consequence, we would expect some jobseekers in Stratford (the high-unemployment area) to choose to search for jobs in central London (the high-vacancy area), thus raising the unemployment outflow in Stratford, and at the same time raise applications per job in central London, then lowering the unemployment outflow around Kings Cross.

Table 8 illustrates the impact of this improved transport link at various distances from King’s Cross and Stratford. As expected, applications per job rise both in King’s Cross and its close vicinity (see column 1, rows 1 and 2), as central London is now attracting more jobseekers from Stratford and surrounding areas. As a consequence, the vacancy outflow increases (column 2) and the locals are less likely to find jobs (column 3), as they face stronger job competition from new applicants attracted by the faster transport link. In row 3, we find that applications per job also rise in Stratford. Despite the fact that some workers are quitting Stratford to search for jobs in central London, the more efficient transport link now attracts some other workers from surrounding wards. But the unemployment outflow still increases as the opportunity to find jobs away from Stratford dominates the effect of increased job competition from elsewhere. Row 4 shows that within 3 km from Stratford (and excluding Stratford itself), applications per job and the vacancy outflow fall, and the unemployment outflow increases, all driven by the possibility of finding new jobs elsewhere. It should be noted however that, quantitatively, the impact on the unemployment outflow is always very small, whether positive or negative, and becomes negligible beyond 3 km from either transport node (rows 5 and 6).

Spillovers on the unemployment outflow around King’s Cross and Stratford are illustrated in more detail on a map in Figure 4, where darker and lighter shades correspond to an increase and a decrease, respectively, in the unemployment outflow. The map once again shows that making it easier for workers in a suburban, high-unemployment area to reach the city centre raises the unemployment outflow in the suburbs and depresses the unemployment outflow in the centre, with declining intensity as one moves away from either transport node. Overall, as a consequence of ripple effects, the impact on the unemployment outflow is very modest (ranging from $-0.66\%$ to $0.55\%$), but it propagates quite widely around the target.

7 Conclusions

This paper develops a model of job search across space that allows, in a tractable way, estimation of a market process with a far larger number of inter-connected market segments than has previously been achieved in the literature. Using data on unemployment and vacancies to estimate a matching function at the census tract level, we find that unemployed workers’ search efforts are strongly discouraged by distance to target jobs. Our estimates
imply that the probability that a random job 5km distant is preferred to a random job in the worker’s residential location is only 11%, and equivalent conclusions are obtained when distance is measured using commuting time or commuting costs. Also, workers are significantly discouraged from applying to jobs in areas in which they expect relatively strong competition from other jobseekers. Constant returns in matching markets are not rejected, and in particular the total number of job applications made in this economy does not respond to the absolute size of the vacancy pool. Commuting flows predicted by the estimated model replicate fairly accurately actual commuting patterns across Census wards, although our model tends to underpredict the proportion of individuals who live and work in the same ward. We finally use our estimates to simulate the impact of local development policies like local stimulus to labor demand or improved transportation links. Despite the fact that labor markets are relatively ‘local’, location-based policies turn out to be rather ineffective in raising the local unemployment outflows, because labor markets overlap and the associated ripple effects in applications largely dilute the effect of local shocks across space. Explicit hiring subsidies for the local unemployed are instead more effective because they increase locals’ ability to win the competition for jobs.

References


Appendices

For online publication

A Data coverage

On the worker side, not all jobseekers are claimant-count unemployed, as jobseekers may also be employed, or unemployed but not claiming benefits; and not all the claimant unemployed may be jobseekers (though they are meant to be, according to the rules for benefit entitlement). To get some ideas of the numbers involved, we turn to the UK Labor Force Survey (LFS), which asks a direct question about job search both of those who are currently in and out of employment. In the Spring of 2005 (to give one example), according to the LFS there were about 3.1 million jobseekers in the UK, and total employment was about 28.1 million. Almost exactly half of the jobseekers were not currently employed, and at that time the official figure for the claimant count was about 875,000. In the LFS, approximately 20% of the claimant unemployed do not report looking for work in the past 4 weeks, suggesting that the claimant unemployed represent nearly a quarter of total jobseekers in the economy.

It may be argued that the claimants are among the most intensive jobseekers (see, among others, Flinn and Heckman, 1983, Jones and Riddell, 1999), and thus we weight jobseeker figures in the LFS by the number of reported search methods used. During the 2002-2007 period, the unweighted share of claimants in total jobseekers was 17.6%, while the weighted share was 23.7%. As one would expect, the share of claimants in jobseekers also varies markedly with levels of education, being 15% among college graduates, 21.8% among high school graduates, 24.9% among those who left school at 16, and 35.2% among those with no qualifications. This means that our study is relatively more representative of low-skill labor markets, which tend to be more local.

For our purpose it is also important to know the fraction of jobseekers who are looking for work in the past 4 weeks. In the LFS, approximately 20% of the claimant unemployed do not report looking for work in the past 4 weeks, suggesting that the claimant unemployed represent nearly a quarter of total jobseekers in the economy.

21 We need to expand the sample period here in order to improve precision of the statistics reported.
at the vacancies recorded in our data, i.e. vacancies advertised at Jobcentres. According to information on job-search methods used, during 2002-2007, 92% of claimants use Jobcentres, and 45.2% of them report Jobcentres as their most important job-search method. These proportions fall to 44.4% and 18.3% for the non-claimant unemployed, and to 19.1% and 5.9% respectively for the employed. Thus, Jobcentres are widely-used by the jobseekers in our sample. In this regard, it is also important to realize that the UK Public Employment Service is much more widely used than the US equivalent. Manning (2003, Table 10.5) shows that only 22% of the US unemployed report using the PES compared to 75% of the UK unemployed, and OECD (2000, Table 4.2) shows that the market share of the PES in the US in vacancy coverage and total hires is substantially lower than in the UK. So, unlike the US, UK job centres do play an important role in matching jobseekers and vacancies.

On the job vacancy side, to assess the representativeness of Jobcentre data we use information from the Vacancy Survey of the Office for National Statistics, which provides comprehensive estimates of the number of job vacancies in the UK, obtained from a sample of about 6,000 employers every month. Employers are asked how many job vacancies there are in their business, for which they are actively seeking recruits from outside the business. These vacancy data cover all sectors of the economy except agriculture, forestry and fishing, but are not disaggregated at the occupation or area level, so we can only make aggregate comparisons between ONS and Jobcentre vacancy series.

On average, since April 2004, the Jobcentre vacancy series in the UK is about two thirds the ONS series, but there are reasons to believe that such proportion may be overstated (Machin, 2001). In particular, in May 2002, an extra question was added to the ONS Vacancy Survey, on whether vacancies reported had also been notified at Jobcentres, and based on this information the ratio of total vacancies advertised at Jobcentres was 44%. While one should allow for sampling variation (this information is only available for May 2002, and for only 420 respondents), this 44% proportion is markedly lower that the two thirds recorded for the post-2004 period. According to Machin (2001), the main reason for this discrepancy is that
Jobcentre vacancies obtained from the computerized system may include vacancies which are “awaiting follow-up”, but which have already been filled by employers, or which have been suspended by the Jobcentres, as it appears that sufficient potential recruits have already been referred. Our vacancy series obtained from Jobcentres (“live unfilled vacancies”) excludes suspended vacancies, but “may still include some vacancies which have already been filled or are otherwise no longer open to recruits, due to natural lags in procedures for following up vacancies with employers”, thus one can still imagine that two-thirds is indeed an upper bound for the fraction of job openings that are effectively available to jobseekers at Jobcentres. As no occupation breakdown is available for the ONS vacancy series, it is not possible to determine how the skill distribution of our vacancy data compares to that of the whole economy, but it is very likely that Jobcentre vacancies over-represent less-skilled jobs.

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22 https://www.nomisweb.co.uk/articles/showArticle.asp?title=<strong>warning: limitations of data</strong>&article=ref/vacs/warning-unfilled.htm
Figure 1
Effect of a doubling in the number of vacancies in Stratford on the unemployment outflow, percentage change

All Figures are best viewed in color print
Figure 2
Recent changes in the vacancy inflow (Panel A) and the unemployment outflow (Panel B) in and around Stratford

Notes: All series are smoothed using moving averages with a 3-month window and equal monthly weights, and normalized to their January 2009 values.

Figure 3
Effect of a doubling in the number of vacancies in Stratford on the unemployment outflow (percentage change), combined with hiring targets for the local unemployed

Notes: The increase in the unemployment outflow rate is always higher than 90% in the target area and lower than 8% outside the target area – so there are no areas in which the outflow rate changes by 8-90%.
Figure 4
Effect of halving the cost of distance between King’s Cross and Stratford on the unemployment outflow, percentage change.
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Notes. The Table provides estimates for equation (2) in the text. Sample: England and Wales, May 2004-April 2006. Standard errors are reported in brackets.
### Table 2
Matching functions in log and level

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<td>(-0.0129)</td>
<td>(0.0132)</td>
</tr>
<tr>
<td>$U_b/\tilde{U}_{10b}$</td>
<td>0.781***</td>
<td>0.307***</td>
<td>0.397***</td>
<td>0.642***</td>
<td>0.311***</td>
</tr>
<tr>
<td></td>
<td>(-0.0575)</td>
<td>(0.0934)</td>
<td>(0.0943)</td>
<td>(-0.1450)</td>
<td>(0.1405)</td>
</tr>
<tr>
<td>$U_{5b}/\tilde{U}_{10b}$</td>
<td>0.252***</td>
<td>0.092**</td>
<td>0.086*</td>
<td>0.192***</td>
<td>0.121***</td>
</tr>
<tr>
<td></td>
<td>(-0.0269)</td>
<td>(0.0448)</td>
<td>(0.0456)</td>
<td>(-0.0648)</td>
<td>(0.0640)</td>
</tr>
<tr>
<td>$V_b/\tilde{V}_{10b}$</td>
<td>-0.962***</td>
<td>-0.420***</td>
<td>-0.349***</td>
<td>-0.853***</td>
<td>-0.521***</td>
</tr>
<tr>
<td></td>
<td>(-0.0484)</td>
<td>(0.1043)</td>
<td>(0.1056)</td>
<td>(-0.1140)</td>
<td>(0.1155)</td>
</tr>
<tr>
<td>$V_{5b}/\tilde{V}_{10b}$</td>
<td>-0.0846***</td>
<td>0.018</td>
<td>0.0036</td>
<td>-0.0153</td>
<td>-0.062</td>
</tr>
<tr>
<td></td>
<td>(-0.0238)</td>
<td>(0.0387)</td>
<td>(0.0394)</td>
<td>(-0.0575)</td>
<td>(0.0574)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Observations</th>
<th>197579</th>
<th>197579</th>
<th>208717</th>
<th>8282</th>
<th>8708</th>
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</thead>
<tbody>
<tr>
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<td>Log</td>
<td>Level</td>
<td>Level</td>
<td>Log</td>
<td>Level</td>
</tr>
<tr>
<td>Time effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Sample</td>
<td>Non-zero Outflow</td>
<td>Non-zero Outflow</td>
<td>All</td>
<td>Feb 2005; Non-zero outflow</td>
<td>Feb 2005; All</td>
</tr>
</tbody>
</table>

Notes. Columns (1) and (4) provide estimates for equation (2) in the text. Columns (2), (3) and (5) provide estimates for the exponential of equation (2) in the text. Sample: England and Wales, May 2004-April 2006 in columns (1)-(3) and February 2005 in column (5). Standard errors are reported in brackets.

### Table 3
Estimates of a job application model with an urn-ball matching function.
Sample averages over May 2004-April 2006

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>Max</th>
<th>No. months</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\delta$</td>
<td>0.300</td>
<td>0.064</td>
<td>0.209</td>
<td>0.470</td>
<td>24</td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.745</td>
<td>0.035</td>
<td>0.652</td>
<td>0.793</td>
<td>24</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>-0.068</td>
<td>0.075</td>
<td>-0.175</td>
<td>0.064</td>
<td>24</td>
</tr>
<tr>
<td>Constant ($\alpha$)</td>
<td>-0.766</td>
<td>0.192</td>
<td>-1.055</td>
<td>-0.419</td>
<td>24</td>
</tr>
</tbody>
</table>

Notes. The Table reports mean estimates of the parameters $\delta$, $\beta$, $\gamma$ and $\alpha$ across the 24 months from May 2004-April 2006, together with standard deviations, minimum and maximum values. Monthly estimates are maximum likelihood estimates of equation (15), where the number of applications per job is given in equation (10).
### Table 4
Estimates of a job application model – Alternative specifications for February 2005

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\delta$</td>
<td>0.259***</td>
<td>0.226***</td>
<td>0.241***</td>
<td>0.263***</td>
<td>0.204***</td>
<td>0.766***</td>
<td>0.260***</td>
<td>0.350***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.058)</td>
<td>(0.070)</td>
<td>(0.069)</td>
<td>(0.059)</td>
<td>(0.029)</td>
<td>(0.117)</td>
<td>(0.038)</td>
<td>(0.070)</td>
<td></td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.747***</td>
<td>0.793***</td>
<td>0.770***</td>
<td>0.799***</td>
<td>0.758***</td>
<td>0.756***</td>
<td>0.745***</td>
<td>0.752***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.064)</td>
<td>(0.076)</td>
<td>(0.087)</td>
<td>(0.050)</td>
<td>(0.039)</td>
<td>(0.042)</td>
<td>(0.044)</td>
<td>(0.045)</td>
<td></td>
</tr>
<tr>
<td>$\gamma$</td>
<td>-0.043</td>
<td>-0.067</td>
<td>-0.009</td>
<td>-0.038</td>
<td>-0.060</td>
<td>-0.053</td>
<td>-0.048</td>
<td>-0.036</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.087)</td>
<td>(0.121)</td>
<td>(0.131)</td>
<td>(0.086)</td>
<td>(0.086)</td>
<td>(0.084)</td>
<td>(0.057)</td>
<td>(0.048)</td>
<td></td>
</tr>
<tr>
<td>$\mu$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.783***</td>
<td></td>
<td></td>
<td>(0.182)</td>
</tr>
<tr>
<td>$\zeta$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-7.702***</td>
<td></td>
<td>(2.536)</td>
</tr>
<tr>
<td>Constant ($\alpha$)</td>
<td>-0.771***</td>
<td>-0.770***</td>
<td>-0.777***</td>
<td>-1.004***</td>
<td>-0.754***</td>
<td>-0.762***</td>
<td>-0.758***</td>
<td>-0.792***</td>
<td>-0.899***</td>
</tr>
<tr>
<td></td>
<td>(0.141)</td>
<td>(0.167)</td>
<td>(0.151)</td>
<td>(0.110)</td>
<td>(0.123)</td>
<td>(0.123)</td>
<td>(0.083)</td>
<td>(0.061)</td>
<td>(0.026)</td>
</tr>
<tr>
<td>$U_b/V_b$</td>
<td>0.044***</td>
<td>0.026</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.087***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.025)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.013)</td>
<td></td>
</tr>
<tr>
<td>$V_b$</td>
<td>-0.020</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
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<td>8709</td>
</tr>
<tr>
<td>Adjusted R2</td>
<td>0.0395</td>
<td>0.0302</td>
<td>0.0305</td>
<td>0.0391</td>
<td>0.0377</td>
<td>0.0374</td>
<td>0.0410</td>
<td>0.0413</td>
<td>0.0109</td>
</tr>
<tr>
<td>Distance concept</td>
<td>Geographic</td>
<td>Geographic</td>
<td>Geographic</td>
<td>Geographic</td>
<td>Time</td>
<td>Cost</td>
<td>Geographic</td>
<td>Geographic</td>
<td>__</td>
</tr>
<tr>
<td>MF specification</td>
<td>Urn-ball</td>
<td>Urn-ball</td>
<td>Urn-ball</td>
<td>Log-linear</td>
<td>Urn-ball</td>
<td>Urn-ball</td>
<td>Urn-ball</td>
<td>Urn-ball</td>
<td>Urn-ball</td>
</tr>
</tbody>
</table>

Notes. The table reports maximum likelihood estimates of the matching function (see equation (15) for the main specification), where the number of applications per job is given in equation (10). Standard error corrected for spatial correlation are reported in brackets.
### Table 5
The distribution of actual and predicted commuting flows

<table>
<thead>
<tr>
<th>Distance</th>
<th>Actual</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 km</td>
<td>23.7</td>
<td>10.1</td>
</tr>
<tr>
<td>(0,5] km</td>
<td>29.5</td>
<td>44.4</td>
</tr>
<tr>
<td>(5,10] km</td>
<td>18.4</td>
<td>25.5</td>
</tr>
<tr>
<td>(10,20] km</td>
<td>15.5</td>
<td>13.3</td>
</tr>
<tr>
<td>20+ km</td>
<td>12.9</td>
<td>6.7</td>
</tr>
<tr>
<td>Total</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

Notes. Actual commuting flows are obtained from the 2001 Census, and predicted commuting flows are obtained from equation (22), evaluated at parameter values reported in column (1) of Table (4).

### Table 6
The propagation of local shocks

<table>
<thead>
<tr>
<th>Distance</th>
<th>Applications per job</th>
<th>Vacancy outflow</th>
<th>Unemployment outflow</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 km</td>
<td>-2.16</td>
<td>98.90</td>
<td>0.40</td>
</tr>
<tr>
<td>(0,5] km</td>
<td>-1.88</td>
<td>-0.48</td>
<td>0.66</td>
</tr>
<tr>
<td>(5,10] km</td>
<td>-1.33</td>
<td>-0.34</td>
<td>0.66</td>
</tr>
<tr>
<td>(10,20] km</td>
<td>-0.76</td>
<td>-0.19</td>
<td>0.45</td>
</tr>
<tr>
<td>(20,35] km</td>
<td>-0.27</td>
<td>-0.07</td>
<td>0.18</td>
</tr>
<tr>
<td>(35,50] km</td>
<td>-0.04</td>
<td>-0.01</td>
<td>0.04</td>
</tr>
<tr>
<td>50+ km</td>
<td>-0.00</td>
<td>-0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Notes: The Table shows the simulated effect of a doubling in the number of vacancies in Stratford and New Town Ward, using the estimates from column 1 of Table 5 (having set $\gamma = 0$).
### Table 7
The propagation of local shocks – with targets for the local unemployed

<table>
<thead>
<tr>
<th>Distance</th>
<th>Applications per job</th>
<th>Vacancy outflow</th>
<th>Unemployment outflow</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 km</td>
<td>-18.30</td>
<td>90.03</td>
<td>102.03</td>
</tr>
<tr>
<td>(0,5] km</td>
<td>-15.52</td>
<td>-4.19</td>
<td>101.74</td>
</tr>
<tr>
<td>(5,10] km</td>
<td>-9.15</td>
<td>-2.42</td>
<td>5.93</td>
</tr>
<tr>
<td>(10,20] km</td>
<td>-4.14</td>
<td>-1.06</td>
<td>3.03</td>
</tr>
<tr>
<td>(20,35] km</td>
<td>-0.95</td>
<td>-0.21</td>
<td>0.51</td>
</tr>
<tr>
<td>(35,50] km</td>
<td>0.94</td>
<td>0.29</td>
<td>-0.78</td>
</tr>
<tr>
<td>50+ km</td>
<td>1.45</td>
<td>0.45</td>
<td>-1.34</td>
</tr>
</tbody>
</table>

Notes: The Table shows the simulated effect of a doubling in the number of vacancies in Stratford and New Town Ward, combined with an increase in the utility of applying to jobs in Stratford of 0.002 for unemployed workers located within 5 km from Stratford. Estimates used are those from column 1 of Table 5 (having set \( \gamma = 0 \)).

### Table 8
The effect of reducing the cost of distance

<table>
<thead>
<tr>
<th>Distance</th>
<th>Percentage change</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Applications per job</td>
</tr>
<tr>
<td>King’s Cross</td>
<td>4.38</td>
</tr>
<tr>
<td>(0,3] km from King’s Cross</td>
<td>1.39</td>
</tr>
<tr>
<td>Stratford</td>
<td>1.73</td>
</tr>
<tr>
<td>(0,3] km from Stratford</td>
<td>-0.59</td>
</tr>
<tr>
<td>(3,10] km from both</td>
<td>0.13</td>
</tr>
<tr>
<td>10+ km from both</td>
<td>-0.02</td>
</tr>
</tbody>
</table>

Notes: The Table shows the simulated effect of halving the cost of distance between King’s Cross Ward and Stratford and New Town Ward. The simulation uses estimates from column 1 of Table 5 (having set \( \gamma = 0 \)).
B. Appendix Figures and Tables

Figure A1
Unemployment to vacancy ratios in England and Wales
Shades correspond to quartiles.
Figure A2
Main parameter estimates over the sample period May 2004-April 2006
Table A1
Descriptive statistics on local labor markets

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>St. dev.</th>
<th>No. Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment stock</td>
<td>105.7</td>
<td>147.4</td>
<td>210755</td>
</tr>
<tr>
<td>Unemployment inflow</td>
<td>20.4</td>
<td>24.6</td>
<td>210755</td>
</tr>
<tr>
<td>Unemployment outflow</td>
<td>19.7</td>
<td>23.8</td>
<td>210755</td>
</tr>
<tr>
<td>Vacancy stock</td>
<td>91.0</td>
<td>227.4</td>
<td>210755</td>
</tr>
<tr>
<td>Vacancy inflow</td>
<td>28.1</td>
<td>72.1</td>
<td>210755</td>
</tr>
<tr>
<td>Vacancy outflow</td>
<td>28.8</td>
<td>73.2</td>
<td>210755</td>
</tr>
</tbody>
</table>

Table A2
Estimates of a job application model – Average values for May 2004-April 2006

To be completed.
Table A3
Average commuting times in the UK

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>No. Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Not on new job</td>
<td>24.5</td>
<td>22.2</td>
<td>612787</td>
</tr>
<tr>
<td>On new job, found via:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reply to advert</td>
<td>24.5</td>
<td>21.6</td>
<td>16059</td>
</tr>
<tr>
<td>Job centre</td>
<td>24.5</td>
<td>20.2</td>
<td>4491</td>
</tr>
<tr>
<td>Careers office</td>
<td>30.2</td>
<td>26.1</td>
<td>453</td>
</tr>
<tr>
<td>Jobclub</td>
<td>25.6</td>
<td>25.6</td>
<td>61</td>
</tr>
<tr>
<td>Private agency</td>
<td>34.6</td>
<td>26.4</td>
<td>4859</td>
</tr>
<tr>
<td>Personal contact</td>
<td>23.2</td>
<td>23.0</td>
<td>15523</td>
</tr>
<tr>
<td>Direct application</td>
<td>22.4</td>
<td>21.7</td>
<td>9646</td>
</tr>
<tr>
<td>Some other method</td>
<td>27.7</td>
<td>26.7</td>
<td>5618</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>24.5</td>
<td>22.3</td>
<td>669497</td>
</tr>
</tbody>
</table>