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

Alan Manning Barbara Petrongolo

Online Appendix

A Data coverage

By covering unemployment and vacancies from the UK Public Employment Service (PES), our data may not fully represent jobseekers and vacancies in the economy. On the worker side, not all jobseekers are claimant 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 form an idea of data coverage, 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,[1] the unweighted share of claimants in total jobseekers was 17.6%, while the weighted share was 23.7%. 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 at the vacancies recorded in our data, i.e. vacancies advertised at PES 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 should be noted that the UK PES 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. Hence the UK PES does 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.

[1] We need to expand the sample period here in order to improve precision of the statistics reported.

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",[2] 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 plausible that Jobcentre vacancies over-represent less-skilled jobs.

B Proof of contraction mappings

B.1 Exogenous Wage Model

To prove that (8) is a contraction mapping, we use Blackwell's sufficient conditions of monotonicity and discounting (Stokey and Lucas, 1989, p. 54). (8)

[2] https://www.nomisweb.co.uk/articles/showArticle.asp?title=warning: limitations of data&article=ref/vacs/warning-unfilled.htm

is a function that maps one set of applications into another set, and is a valid mapping for all vectors in the positive orthant. We rewrite it in log form:

$$\begin{aligned}T(a_b) &= \ln A_b = \frac{1}{1+k}\left\{k\ln\Psi\left(e^{a_b}\right)+\ln\left[\sum_a U_a W_b f_{ab}\left[\sum_{b'} V_{b'}W_{b'}f_{ab'}\left(\frac{\Psi\left(e^{a_{b'}}\right)}{e^{a_{b'}}}\right)^k\right]^{\gamma-1}\right]\right\} \\ &= \frac{1}{1+k}\left\{k\ln\Psi\left(e^{a_b}\right)+\ln\left[\sum_a U_a W_b f_{ab} C_a(a)^{\gamma-1}\right]\right\},\end{aligned}$$

where $f_{ab} == e^{\delta_0-\delta d_{ab}}\widehat{IV}_{ab}$ and

$$C_a(a) = \left[\sum_{b'} V_{b'}W_{b'}f_{ab'}\left(\frac{\Psi\left(e^{a_b}\right)}{e^{a_b}}\right)^k\right].$$

This clearly satisfies monotonicity. As we assume $p'(A)<0$, $\Psi'(A)>0$, and $p(A)=\frac{\Psi(A)}{A}$ we must have $\epsilon_{\Psi A}(A)\equiv\frac{\partial\log\Psi(A)}{\partial\log A}<1$. If $0\le\epsilon_{\min}\le\epsilon_{\Psi A}\le\epsilon_{\max}\le 1$, we have that:

$$C_a(a+\alpha)\ge C_a(a)\,e^{-k(1-\epsilon_{\min})\alpha},$$

which implies:

$$\left[\sum_a U_a W_b f_{ab} C_a(a+\alpha)^{\gamma-1}\right]\le e^{-(\gamma-1)k(1-\epsilon_{\min})\alpha}\left[\sum_a U_a W_b f_{ab} C_a(a)^{\gamma-1}\right].$$

This in turn implies

$$T(a_b+\alpha)-T(a_b)\le\alpha\frac{k}{1+k}\left[\epsilon_{\max}+(1-\gamma)(1-\epsilon_{\min})\right].$$

For our parameter values, this satisfies discounting.

B.2 Endogenous Wage Model

To prove that (20) is a contraction mapping, note first that it satisfies monotonicity because both its right- and left-hand sides are increasing in applications.

To prove discounting, define $Z(\widetilde{A})$ to be the log of the right-hand side of (20), i.e.:

$$Z(\widetilde{A}) = \ln\left(\widetilde{c}\widetilde{W}_b^{k\rho}\right) + \ln\left(\sum_a U_a f_{ab}\left[\sum_{b'} V_{b'} e^{-k\tilde{A}_{b'}} \widetilde{W}_{b'}^{k\rho} f_{ab'}\right]^{\gamma-1}\right),$$

which implies:

$$Z(\widetilde{A}+\alpha) = Z(\widetilde{A}) + k\,(1-\gamma)\,\alpha.$$

Consider the left-hand side of (20), which can be written as:

$$\ln(T) + kT = Z.$$

This can be thought of as giving a mapping $T(Z)$ where:

$$T'(Z) = \frac{T(Z)}{1+kT(Z)}.$$

From the mean value theorem we have that:

$$\begin{aligned} T\left(Z\left(\widetilde{A}+\alpha\right)\right) &= T\left(Z\left(\widetilde{A}\right)\right) + T'\left(\widetilde{Z}\right)\left[Z\left(\widetilde{A}+\alpha\right) - Z\left(\widetilde{A}\right)\right] \\ &= T\left(Z\left(\widetilde{A}\right)\right) + T'\left(\widetilde{Z}\right) k\,(1-\gamma)\,\alpha \\ &= T\left(Z\left(\widetilde{A}\right)\right) + \frac{(1-\gamma)\,kT\left(\widetilde{Z}\right)}{1+kT\left(\widetilde{Z}\right)}\alpha < \alpha, \end{aligned}$$

which satisfies discounting.

C Standard Errors

This section outlines in more detail the two methods we use to compute the standard errors. The first measure (s.e.$_1$) is obtained as the standard deviation of the monthly parameter estimates. Assuming that parameters are stable across months is a necessary condition for this procedure to be valid.

If the data used are serially correlated, one might expect that the parameter estimates themselves may be serially correlated, and that their standard errors need to be adjusted for this fact. However Table A6 shows that the serial correlation (of first and second order) in the estimates is small and never significant so the reported standard errors are nor adjusted for serial correlation.

The second measure of standard errors (s.e.$_2$) reports the "sandwich" standard error obtained from the non-linear least squares estimator, allowing for possible heteroskedasticity and spatial correlation in the residuals, but assuming that the true covariance between residuals from areas more than 100 km apart is zero. Our estimated variance-covariance matrix of the parameters is given by $\widehat{V} = \widehat{H}^{-1}(\widehat{G}'\widehat{\Omega}\widehat{G})\widehat{H}^{-1}$, where $\widehat{H}$ is the Hessian of the objective function, $\widehat{G}$ is the Jacobian, and the spatial correlation matrix $\widehat{\Omega}$ is the product matrix of the residuals after imposing the restriction that residuals from areas more than 100 km apart are uncorrelated.

D Descriptive data analysis and link to structural parameter estimates

This Appendix complements our model estimates of Section 4 by highlighting the role of various aspects of the data in explaining specific structural parameters. We process in three steps. First, we provide descriptive evidence on local matching patterns by estimating a conventional, reduced-form, matching function, augmented for local spillovers. Second, we obtain a restricted version of our structural model, which delivers a closed-form solution for the outflow rate and thus a clearer correspondence between data and model parameters. Third, we link monthly variation in our structural parameter estimates to monthly variation in the reduced-form matching function estimates, in the spirit of Andrews, Gentzkow and Shapiro (forthcoming).

D.1 Regression Models for the Vacancy Outflow Rate

In our reduced-form matching function specification, we regress the vacancy outflow rate in a ward on the stocks of unemployment and vacancies in both the local and surrounding wards, treated as exogenous.[3]

Geographic spillovers are captured in the following regression equation:

$$\begin{aligned}\log\left(\frac{M_{b,t}}{V_{b,t}}\right) &= \alpha_0 + \alpha_1 \log(U_{b,t} + \beta_1 U_{5b,t} + \beta_2 U_{10b,t} + \beta_3 U_{20b,t} + \beta_4 U_{35b,t}) \qquad \text{(D1)}\\ &\quad + \alpha_2 \log(V_{b,t} + \gamma_1 V_{5b,t} + \gamma_2 V_{10b,t} + \gamma_3 V_{20b,t} + \gamma_4 V_{35b,t}) + \alpha_3 \log w_b + \varepsilon_{b,t},\end{aligned}$$

where $M_{b,t}$ is the vacancy outflow in 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 5 km and 10 km of ward b, and so on; and similarly for vacancies. w_b denotes ward-level wages relative to mean wages within 10 km, and only varies across wards. This specification implies that the probability of filling a vacancy in b depends on local unemployment and on unemployment in the surrounding areas, whereby $\beta_i < 1$ would imply that more distant unemployed workers are less effective in filling a vacancy in b than local workers. Similarly, more vacancies in b and neighboring wards are expected to reduce the vacancy outflow rate in b, whereby $\gamma_i < 1$ implies that more distant vacancies have a diminishing effect. Specifications similar to (D1) have been estimated by Burda and Profit (1996) for Czech districts, and Burgess and Profit (2001) and Patacchini and Zenou (2007) for UK TTWAs.

We next define the total number of unemployed and vacancies within 10km of b:

$$\widetilde{U}_{10b,t} = U_{b,t} + U_{5b,t} + U_{10b,t}; \qquad \widetilde{V}_{10b,t} = V_{b,t} + V_{5b,t} + V_{10b,t},$$

[3] 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 inconvenient (Gregg, Machin and Manning, 2004, pp. 387-395).

and approximate (D1) by:

$$
\begin{aligned}
\log\left(\frac{M_{b,t}}{V_{b,t}}\right) \approx\; & \alpha_0 + \alpha_1 \log \widetilde{U}_{10b,t} + \alpha_2 \log \widetilde{V}_{10b,t} \\
& + \alpha_1 \left(\frac{1-\beta_2}{\beta_2} \frac{U_{b,t}}{\widetilde{U}_{10b,t}} + \frac{\beta_1-\beta_2}{\beta_2} \frac{U_{5b,t}}{\widetilde{U}_{10b,t}} + \frac{\beta_3-\beta_2}{\beta_2} \frac{U_{20b,t}}{\widetilde{U}_{10b,t}} + \frac{\beta_4-\beta_2}{\beta_2} \frac{U_{35b,t}}{\widetilde{U}_{10b,t}} \right) \\
& + \alpha_2 \left(\frac{1-\gamma_2}{\gamma_2} \frac{V_{b,t}}{\widetilde{V}_{10b,t}} + \frac{\gamma_1-\gamma_2}{\gamma_2} \frac{V_{5b,t}}{\widetilde{V}_{10b,t}} + \frac{\gamma_3-\gamma_2}{\gamma_2} \frac{V_{20b,t}}{\widetilde{V}_{10b,t}} + \frac{\gamma_4-\gamma_2}{\gamma_2} \frac{V_{35b,t}}{\widetilde{V}_{10b,t}} \right) \\
& + \alpha_3 \log w_b + \varepsilon_{b,t}. \qquad \text{(D2)}
\end{aligned}
$$

Specification (D2) has the advantage of being linear in parameters, so instrumental variables and ward fixed-effects can be easily introduced. Returns to scale in the matching function can be assessed by comparing coefficients on $\log \widetilde{U}_{10b,t}$ and $\log \widetilde{V}_{10b,t}$, while coefficients on share variables $U_{b,t}/\widetilde{U}_{10b,t}$,..., $U_{35b,t}/\widetilde{U}_{10b,t}$, and $V_{b,t}/\widetilde{V}_{10b,t}$,..., $V_{35b,t}/\widetilde{V}_{10b,t}$ indicate the relative effectiveness of unemployment and vacancies at different distances. The decision to normalize by unemployment and vacancies within 10 km in (D2) is arbitrary, but it is important to choose a normalization for which β_i and γ_i are not zero, and for which the share variables are not too large. Considering this, 10 km seemed the right choice. On average, about 5% of unemployment and vacancies within 10 km are in the local ward, one-third are within 5 km. Moving beyond the 10 km ring, there are about 4.5 times the number of unemployed and vacancies between 10 and 20 km as within 10 km and 16 times as many within 35 km.

Estimates of specification (D2) are reported in Table A7. 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 0.977 ($= 1 + 0.201 - 0.224$), suggesting (something very close to) constant returns. It is not just the level of unemployment and vacancies within 10 km 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 $U_{b,t}/\widetilde{U}_{10b,t}$ and $U_{5b,t}/\widetilde{U}_{10b,t}$ one can derive an estimate for β_2 of 0.22 and for β_1 of 0.53, i.e. unemployed workers outside the ward but within 5 km have 53% of the matching effectiveness as those within the ward and the unemployed in the 5-10km ring have an effectiveness of 22%. Unemployed in the 20 km and 35 km 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 5 km have 23% of the effectiveness of those within the ward, and vacancies in the 5-10 km ring have an effectiveness of 21%. Vacancies in the 20 km and 35 km rings have very small effects on the vacancy outflow rate. Column 2 introduces time dummies, with a very slight attenuation of all coefficients, but virtually identical conclusions. In both columns the coefficient on relative wages is positive and highly significant.

While this is the standard approach in the empirical matching function literature, there are concerns on the identification of the parameters of interest. For example, innovations in matching efficiency in an area, as represented by $\varepsilon_{b,t}$, may 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 $\log \widetilde{U}_{10b,t}$ is only slightly lower, while the one on $U_{b,t}/\widetilde{U}_{10b,t}$ 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 $V_{b,t}/\widetilde{V}_{10b,t}$, on which the local vacancy stock has the most influence. Overall, our previous qualitative conclusions on matching elasticities α_1 and α_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-ward variation explains 12% of the total variance. The matching elasticities α_1 and α_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. Column 5 includes region fixed effects, as opposed to ward fixed effects, and the resulting magnitude and significance of local spillovers are virtually unchanged from column 3, which does not include any geographic effects.

The dependent variable in specification (D2) is not defined when the outflow rate is zero. This becomes a relevant issue when using data on very small areas, and indeed the vacancy outflow is zero in 6.2% of observations in our sample. To deal with this we estimate outflow equations like (D2) in levels instead of logs.

Column 1 in Table A8 presents estimates of a log-linear matching function, having excluded unemployment and vacancies beyond 10km, as the estimates in Table A7 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 column 1. 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. Columns 4 and 5 report results for the log-linear and linear models estimated for one month only (February 2005), as done for some of the estimates of Section 4.

The results of Tables A7 and A8 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 10 km 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 more local to them, say 5 km away, which then become harder to obtain, and causing workers 5 km 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 and the evaluation of local intervention. Our structural model provides insight into the structure of local spillovers.

D.2 The Model: A Special Case

One feature of our structural model that makes it hard to visualize the link between parameter estimates and specific data features is the absence of a closed-form solution. In this subsection we consider a special case which instead delivers a closed-form solution and thus a clearer correspondence between data and model parameters.

Let's consider the model for job applications in (18), and impose that unemployment, vacancies and wages are equal across areas. Define $D_b = \sum_a e^{-\delta^* d_{ab}} IV_{ab}^k$ and assume that this is constant for all b i.e. that $D_b = D$. This amounts to the assumption that every areas is as well-connected as any other which would be the case if areas were regularly spaced on a sphere. Under these assumptions, vacancies in all areas receive the same number of applications. Using (18), this is given by:

$$\tilde{A} = \widetilde{c}\widehat{W}^{k\rho_1} e^{-k\tilde{A}} UD \left[V e^{-k\tilde{A}} \widehat{W}^{k\rho_1} D \right]^{\gamma-1},$$

which can be re-arranged to give:

$$\tilde{A} e^{\gamma k \tilde{A}} = \widetilde{c} D^{\gamma} \widehat{W}^{\gamma k \rho_1} \left(\frac{U}{V} \right) V^{\gamma}. \tag{D3}$$

Equation (D3) states that applications rise with the U-V ratio. Conditional on the U-V ratio, the effect of the number of vacancies depends on the returns to scale in matching (γ), and is positive, zero or negative in case of increasing, constant or decreasing returns, respectively; and similarly for the impact of wages on applications. One can derive a similar expression if one assume that the cost of travelling between wards is infinitely high and all individuals live and work in the same ward and the cost of within-ward travel is zero - in this case one would have $D = 1$.[4]

The number of applications is unobserved, but is linked to the vacancy outflow rate through (17), which can be rewritten in log-linear form:

$$\ln \frac{M}{V} = \ln \lambda + \ln \left(1 - e^{-\tilde{A}}\right). \tag{D4}$$

Using (D3) and (D4), we obtain the partial effects of the U-V ratio and the number of vacancies on the vacancy outflow rate:

$$\begin{aligned} \frac{\partial \ln(M/V)}{\partial \ln(U/V)} &= \frac{\tilde{A}e^{-\tilde{A}}}{1 - e^{-\tilde{A}}} \frac{1}{1 + \gamma k \tilde{A}}, && \text{(D5)} \\ \frac{\partial \ln(M/V)}{\partial \ln V} &= \gamma \frac{\partial \ln(M/V)}{\partial \ln(U/V)}. && \text{(D6)} \end{aligned}$$

We next show evidence on these model predictions.

D.3 Linking Structural and Non-Structural Parameter Estimates

This section aims to provide a mapping from the data to the parameters of interest following the approach of Gentzkow and Shapiro (2017). We do so by linking our structural parameter estimates to regression coefficients from reduced-form regressions, which have a clear partial-effect interpretation. Specifically, we estimate for each month in the sample a slightly modified version of the linear regression model (D2):

[4] If, however, wages vary across areas, areas with higher wages attract more applications even under constant returns.

$$\log\left(\frac{M_{b,t}}{V_{b,t}}\right) = \alpha_{0t} + \alpha_{1t}\log\frac{\widetilde{U}_{10b,t}}{\widetilde{V}_{10b,t}} + \alpha_{2t}\log\widetilde{V}_{10b,t} + \alpha_{3t}\left(\frac{U_{b,t}}{\widetilde{U}_{10b,t}} - \frac{V_{b,t}}{\widetilde{V}_{10b,t}}\right)$$
$$+\alpha_{4t}\left(\frac{U_{5b,t}}{\widetilde{U}_{10b,t}} - \frac{V_{5b,t}}{\widetilde{V}_{10b,t}}\right) + \alpha_{5t}\log w_b + \varepsilon_{b,t}, \quad \text{(D7)}$$

in which we have dropped unemployment and vacancies beyond 10 km and imposed equal coefficients on $U_{b,t}/\widetilde{U}_{10b,t}$ (respectively $U_{5b,t}/\widetilde{U}_{10b,t}$) and $V_{b,t}/\widetilde{V}_{10b,t}$ (respectively $V_{5b,t}/\widetilde{V}_{10b,t}$). We also use structural parameter estimates for each month (whose averages across months are reported in Table 1). Thus we are left with 24 monthly estimates of reduced-form parameters α_{0t},...,α_{5t}, and 24 monthly estimates of structural parameters δ_t^*, γ_t, ρ_t, λ_t, $\widetilde{c}_t$, and regress each of the structural parameters (or some combination of them) on α_{0t},...,α_{5t}. The results of this exercise are reported in Table A9, and summarized in the following points:

- *Elasticity of the outflow rate to the U-V ratio*: $\frac{\tilde{A}e^{-\tilde{A}}}{1-e^{-\tilde{A}}}\frac{1}{1+\gamma k\tilde{A}}$. According to (D5), the log linear regression coefficient on the U-V ratio (α_{1t}) should be related to the number of applicants per vacancy. Column 1 in Table A8 explores this prediction by regressing the right-hand side of (D5) – as predicted by structural estimates[5] – on α_{0t},...,α_{5t}. Variation in dependent variable loads most heavily on α_{1t}, implying that job applications are closely linked to the elasticity of the outflow rate with respect to the U-V ratio, as predicted by (D5).

- *Returns to scale parameter*: γ_t. According to (D6), γ_t should be negatively related to the coefficient on the U-V ratio (α_{1t}) and positively related to the coefficient on vacancies (α_{2t}). These correlation patterns are validated by results of column 2, although α_{3t} also has a significant impact on γ_t. A plausible reason is that the unrestricted application model is more complex than the restricted model of the previous subsection.

[5] Specifically we obtain $\tilde{A}_t$ using (18) and take averages across wards for each month.

- *Wage parameter*: ρ_t. Column 3 shows that this is mostly related, as it is to be expected, to the regression coefficient on wages, α_{5t}.

- *Scale parameter in applications*: (log) λ_t. According to (D4), λ plays the role of an intercept in an outflow rate outflow, and column 4 shows that the monthly estimate α_{0t} is indeed the parameter that has the strongest effect on λ_t.

- *Cost of distance parameter*: δ_t. The role of δ_t cannot be visualized in the restricted model of the previous subsection, which essentially assumes distance away, but – intuitively – it should be influenced by the relative importance of near and distant unemployment and vacancies in predicting vacancy outflows. Indeed column 5 shows that δ_t is more strongly influenced by α_{3t} than α_{4t}.

In summary, the correlations reported in Table A9 provide clear evidence on identification of structural parameters of our job search model by highlighting links with relevant features of the data.

References

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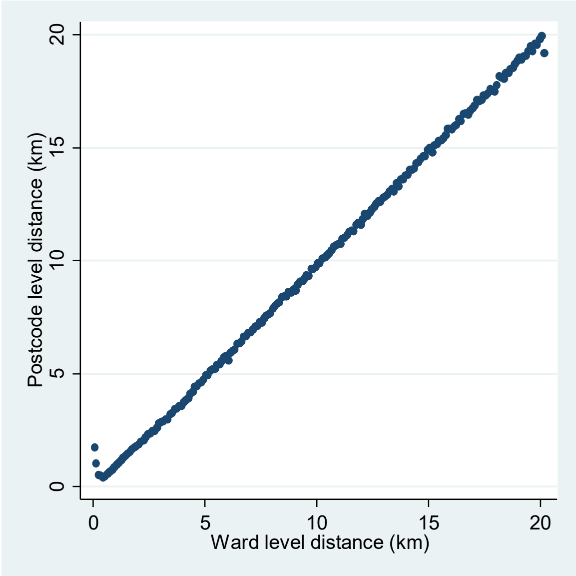
D. Appendix Figures and Tables

Figure A1
Unemployment to vacancy ratios in England and Wales
Shades correspond to quartiles.

Figure A2
Scatterplot (by 100-metre bins) of postcode-based distance against ward-level distance



Notes. Each observation refers to a 100-meter bin. Source: ASHE.

Table A1
Descriptive statistics on local labor markets: Means and standard deviations

Variable	Mean	Standard deviation			No. Obs.
		Overall	Within ward	Within month	
Unemployment stock	106.5	147.8	14.9	147.7	208,762
Vacancy stock	91.9	228.3	61.3	228.0	208,762
Vacancy outflow	29.1	73.5	33.0	73.4	208,762
Vacancy Outflow Rate	0.331	0.201	0.184	0.198	208,762
U-V Ratio	3.69	8.03	5.23	8.00	208,762
Area	17.0	28.3	-	-	8,850
Wages	9.08	0.90	-	-	8,850

Notes. The sample includes CAS 2003 wards in England and Wales. Unemployment and vacancy variables are at monthly frequency (May 2004-April 2006) and are obtained from NOMIS. Area measures ward size in square km and is obtained from the 2001 Census. Wages are predicted based on the local industry composition of employment, combining information on the ward-level industry composition from BRES with median hourly wages by industry from ASHE. Due to small sample issues, predicted wages have been averaged at the ward-level. The overall standard deviation is across all ward-month observations. The standard deviation within ward is obtained after removing ward-level means. The standard deviation within month is obtained after removing month-level means.

Table A2
Descriptive statistics on local labor markets: Correlation Matrices

(A) Raw correlation matrix

	Unemploym.	Vacancies	Vacancy outflow	Vacancy outflow Rate	U-V Ratio
Unemployment	1				
Vacancies	0.366	1			
Vacancy outflow	0.374	0.913	1		
Vacancy Outflow Rate	0.083	-0.028	0.114	1	
U-V Ratio	0.189	-0.127	-0.118	0.115	1

(B) Correlation matrix after removing ward-level means

	Unemploym.	Vacancies	Vacancy outflow	Vacancy outflow Rate	U-V Ratio
Unemployment	1				
Vacancies	-0.144	1			
Vacancy outflow	-0.036	0.626	1		
Vacancy Outflow Rate	0.055	-0.004	0.260	1	
U-V Ratio	0.106	-0.069	-0.047	0.007	1

Notes. See notes to Table A1.

Table A3
Conditional logit estimates for the choice of transport mode

	Mode of transport		
	Walking	Cycling	Public Transport
Constant	-1.0563	-2.5607	-1.527
	(0.00102)	(0.00175)	(0.00073)
Distance	-0.1288	-0.0787	0.0043
	(0.00017)	(0.00024)	(0.00003)

Notes. The coefficients reported are obtained from a conditional logit model where the omitted (base) category is driving. The number of observations is 8.5 million. Source: 2001 Census Special Workplace Statistics.

Table A4
Estimates of a job application and matching model
Sample averages for May 2004-April 2005

	(1)	(2)	(3)	(4)	(5)
Cost of distance (δ^*)	0.220***	0.248***	0.215***	0.220***	
	(0.026)	(0.034)	(0.027)	(0.028)	
Returns to scale (γ)	-0.160***		-0.176***	-0.145***	
	(0.038)		(0.039)	(0.033)	
Wage elasticity (ρ)	0.920***	1.150***	0.942**	1.025***	
	(0.373)	(0.410)	(0.378)	(0.261)	
Matching effectiveness (λ)	0.371***	0.366***	0.371***	0.383***	0.425***
	(0.033)	(0.033)	(0.033)	(0.032)	(0.039)
Scale parameter in $\tilde{A}$ ($\tilde{c}$)	1.185***	0.557***	1.239***	1.075***	
	(0.207)	(0.083)	(0.202)	(0.131)	
Local U_b/V_b (α_1)			0.051		
			(0.043)		
Mismatch (α_2)				0.715*	
				(0.412)	
Number of months	24	24	24	15	24

Notes. Model specifications are the same as in Table 2. Coefficients reported are averages across monthly estimates, with standard deviations reported in brackets. Specification (4) is estimated on the months February 2005-May 2006, as unemployment data by occupation become available in January 2005.

Table A5
Average commuting times in the UK

	Mean	Std. Dev.	No. Obs.
Not on new job	24.4	22.2	620824
On new job, found via:			
Reply to advert	24.5	21.6	16117
Job centre	24.5	20.2	4499
Careers office	30.2	26.1	453
Jobclub	25.6	25.6	61
Private agency	34.6	26.3	4869
Personal contact	23.2	23.0	15639
Direct application	22.4	21.7	9673
Some other method	27.6	26.6	5708
Total	24.5	22.3	677843

Notes. Figures report one-way daily commuting times (in minutes). New jobs are defined by tenure up to three months. Source: Labour Force Survey, 1993-2007.

Table A6
Test for serial correlation in structural parameter estimates

	Dependent variable				
	δ_t^*	γ_t	ρ_t	λ_t	$\tilde{c}_t$
1st order lag	0.115	-0.030	0.075	-0.195	0.219
	(0.220)	(0.213)	(0.212)	(0.269)	(0.210)
Observations	23	23	23	23	23
1st order lag	0.166	-0.057	0.026	-0.103	0.129
	(0.229)	(0.203)	(0.232)	(0.287)	(0.209)
2nd order lag	-0.255	0.442	-0.026	0.277	0.421*
	(0.239)	(0.200)	(0.221)	(0.289)	(0.211)
Observations	22	22	22	22	22

Notes. The estimates reported are obtained from first- and second-order autoregressive models for the monthly parameter estimates summarized in Table 1.

Table A7
Log-linear matching functions with local spillovers

	Dependent variable: (log) vacancy outflow rate				
	(1)	(2)	(3)	(4)	(5)
Estimation method	OLS	OLS	IV	IV	IV
$\log \tilde{U}_{10b}$	0.201***	0.193***	0.178***	0.120**	0.168***
	(0.00440)	(0.00477)	(0.00612)	(0.0581)	(0.00459)
$\log \tilde{V}_{10b}$	-0.224***	-0.214***	-0.191***	-0.159***	-0.190***
	(0.00528)	(0.00573)	(0.00751)	(0.0311)	(0.00521)
$U_b / \tilde{U}_{10b}$	0.714***	0.711***	0.317***	-0.155	0.222***
	(0.0563)	(0.0559)	(0.0798)	(0.415)	(0.0491)
$U_{5b} / \tilde{U}_{10b}$	0.287***	0.281***	0.193***	0.0764	0.196***
	(0.0267)	(0.0267)	(0.0308)	(0.265)	(0.0177)
$U_{20b} / \tilde{U}_{10b}$	-0.00135*	-0.00158**	-4.21e-05	-0.0103	-0.000530
	(0.000770)	(0.000755)	(0.00135)	(0.00982)	(0.000853)
$U_{35b} / \tilde{U}_{10b}$	0.000262**	0.000233**	0.000683**	0.000350	0.000747***
	(0.000108)	(0.000108)	(0.000318)	(0.00221)	(0.000183)
$V_b / \tilde{V}_{10b}$	-0.852***	-0.842***	-0.164***	-0.371**	-0.175***
	(0.0445)	(0.0444)	(0.0508)	(0.144)	(0.0308)
$V_{5b} / \tilde{V}_{10b}$	-0.120***	-0.116***	-0.0588**	-0.0374	-0.0530***
	(0.0240)	(0.0240)	(0.0277)	(0.0882)	(0.0160)
$V_{20b} / \tilde{V}_{10b}$	-0.000699	-0.000531	-0.00618***	-0.00559	-0.00651***
	(0.00106)	(0.00100)	(0.00153)	(0.00408)	(0.000971)
$V_{35b} / \tilde{V}_{10b}$	-2.42e-05	-4.42e-06	-0.00101**	-0.000399	-0.000884***
	(0.000121)	(0.000116)	(0.000434)	(0.00181)	(0.000279)
$\log w_b$	0.169***	0.168***	0.178***		0.180***
	(0.0318)	(0.0318)	(0.0333)		(0.0158)
Observations	197,579	197,579	175,157	175,157	175,157
Time fixed effects	No	Yes	Yes	Yes	Yes
Ward fixed effects	No	No	No	Yes	No
Region fixed effects	No	No	No	No	Yes

Notes. The Table provides estimates for equation (D2). The relative wage coefficient cannot be estimated when ward fixed effects are included as it only varies across wards. Standard errors are clustered by ward and reported in brackets. Sample period: May 2004-April 2006.

Table A8
Matching functions in log and level

	(1)	(2)	(3)	(4)	(5)
Estimation method	OLS	NLLS	NLLS	OLS	NLLS
$\log \widetilde{U}_{10b}$	0.192***	0.178***	0.172***	0.191***	0.167***
	(0.004)	(0.004)	(0.004)	(0.010)	(0.011)
$\log \tilde{V}_{10b}$	-0.212***	-0.220***	-0.171***	-0.205***	-0.162***
	(0.00510)	(0.005)	(0.005)	(-0.012)	(0.013)
$U_b / \widetilde{U}_{10b}$	0.706***	0.502***	0.332***	0.532***	0.196
	(0.0560)	(0.050)	(0.045)	(0.141)	(0.139)
$U_{5b} / \widetilde{U}_{10b}$	0.290***	0.203**	0.201*	0.231***	0.149**
	(0.0264)	(0.024)	(0.023)	(0.065)	(0.062)
$V_b / \tilde{V}_{10b}$	-0.843***	-1.025***	-0.429***	-0.705***	-0.365***
	(0.0444)	(0.040)	(0.035)	(0.102)	(0.102)
$V_{5b} / \tilde{V}_{10b}$	-0.117***	-0.091	-0.031	-0.046	0.045
	(0.0240)	(0.022)	(0.021)	(0.060)	(0.059)
$\log w_b$	0.168***	0.139***	0.0.135***	0.176**	0.073
	(0.0319)	(0.029)	(0.028)	(0.072)	(0.069)
Observations	197579	197579	208717	8282	8708
Functional form	Log	Level	Level	Log	Level
Time effects	Yes	Yes	Yes	No	No
Sample	Non-zero Outflow	Non-zero Outflow	All	Feb 2005; Non-zero outflow	Feb 2005; All

Notes. Columns (1) and (4) provide estimates for equation (D2). Columns (2), (3) and (5) provide estimates for the exponential of equation (D2). Standard errors are clustered by ward and reported in brackets. Sample: May 2004-April 2006 in columns (1)-(3) and February 2005 in column (5).

Table A9
The relationship between structural parameters and coefficients from log-linear regression models

	Dependent variable: Estimates from structural model				
	(1)	(2)	(3)	(4)	(5)
	Elasticity of vacancy outflow rate w.r.t U-V	Returns to scale (γ_t)	Coefficient on wages (ρ_t)	Matching effectiveness (λ_t)	Cost of Distance (δ_t^*)
Constant (α_{0t})	-0.085	-0.116	0.006	0.997***	0.045
	(0.068)	(0.081)	(0.787)	(0.056)	(0.062)
Coef on $\log(\tilde{U}_{10b,t}/\tilde{V}_{10b,t})$ (α_{1t})	1.527***	-0.551**	1.678	0.512***	0.200
	(0.207)	(0.246)	(2.389)	(0.171)	(0.188)
Coef on $\log(\tilde{V}_{10b,t})$ (α_{2t})	0.768	2.123**	10.200	0.116	-0.007
	(0.751)	(0.894)	(8.683)	(0.621)	(0.683)
Coef on $\left(\frac{U_{b,t}}{\tilde{U}_{10b,t}} - \frac{V_{b,t}}{\tilde{V}_{10b,t}}\right)$ (α_{3t})	-0.042	0.100**	0.377	0.102***	0.083**
	(0.035)	(0.042)	(0.406)	(0.029)	(0.032)
Coef on $\left(\frac{U_{5b,t}}{\tilde{U}_{10b,t}} - \frac{V_{5b,t}}{\tilde{V}_{10b,t}}\right)$ (α_{4t})	-0.119	-0.064	-0.861	0.031	0.033
	(0.097)	(0.116)	(1.123)	(0.080)	(0.088)
Coef on $\log(w_{b,t})$ (α_{4t})	-0.072	0.202*	3.650***	0.017	0.011
Observations	24	24	24	24	24
R-squared	0.820	0.548	0.563	0.959	0.445

Notes. The Table reports estimates of linear regression models in which the dependent variable is the monthly estimate of a given parameter of the structural model (or, in the case of column (1), a function of parameters), and the independent variables are regression coefficients from the monthly estimates of the reduced-form model for the vacancy outflow rate reported in equation (D7).