***Please note that figures 2a and 2b on page 20 can only be printed out successfully using postscript. Please contact the CEP if you need a good copy of the figures.**

Abstract

We provide empirical evidence on the nature of spatial externalities in a matching model for the UK. We use a monthly panel of outflows, unemployment and vacancy stocks data from the registers at Jobcentres in the UK; these are mapped on to travel-to-work areas. We find evidence of significant spill-over effects that are generally in line with the predictions of theory. For example, we find that conditional on local labour market conditions, high unemployment levels in neighbouring areas raise the number of local filled vacancies but lower the local outflow from unemployment.

JEL Classification: E24, J64
Keywords: matching model, externalities, spatial dependence, unemployment outflows.

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Externalities in the Matching of Workers and Firms in Britain

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1. Introduction

The matching approach is now one of the standard tools for analysing labour markets. It has proved to be an essential element in understanding the dynamic processes of labour markets for both labour and macroeconomics (see for example the surveys of Mortensen and Pissarides, 1999a and 1999b). However, empirically it is still largely a 'black box' approach. Estimates of matching functions have been mostly from aggregate time series[1], with a focus on looking at the estimated 'returns to scale'[2]. Recently, some authors have used cross-section or panel data[3].

In this paper we extend the empirical evidence on matching functions. First, by establishing the existence of a matching relationship in a large panel dataset, we significantly enhance the empirical support for their use as a key tool of analysis. We look at local labour markets, in fact travel-to-work areas (TTWAs), in a ten year panel of monthly data on unemployment and vacancy stocks and flows in Britain. Second, we provide evidence on a neglected aspect of matching: the importance of the externalities stressed by matching theory. These externalities lead to market inefficiencies and the potential for multiple equilibria. The matching approach is built on the importance of trading frictions, and in labour markets one of the most important is spatial frictions. We test for and find significant spatial inter-dependence between markets, decaying with the distance between them. We also find evidence of significant cyclical variation in the strength of these spatial spillovers. Both of these findings make sense with the assumption that search costs are likely to increase with distance. Search effort is therefore more intense in neighbouring markets, and when agents are in a strong position in the business cycle, they can afford to only search locally.

With a few exceptions the existing empirical studies have not really examined the externalities issue. Burda and Profit (1996) extended the matching function to account for spillovers from neighbouring areas on local employment probabilities. This paper applies their specification of the matching function to local labour markets in Britain, and extends their work, first, by exploring the effects on both unemployment and vacancy flows as dependent variables, and second, by analysing cyclical variations of spatial dependence in job-matching.

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[1] See for example, Pissarides (1986) and Blanchard and Diamond (1989). Other more recent examples are Berman (1997), Fox (1996), Gregg and Petrongolo (1997), Gross (1997), Warren (1996).
[2] See Anderson and Burgess (2000) for whether the sum of the coefficients can be so interpreted.
[3] See for example, Anderson and Burgess (2000), Burda and Profit (1996), Boeri and Burda (1996), Coles and Smith (1996), Münich, Svenjar and Terrell (1995).

We find evidence of significant spill-over effects. For example, we find that conditional on local (TTWA) labour market conditions, high unemployment levels in neighbouring areas raise the number of local filled vacancies but lower the local outflow from unemployment. We also find cyclical variation in the degree of spatial dependence: in a boom, the unemployed reduce their search radius and employers increase theirs; the situation is reversed in a recession.

The rest of the paper is organised as follows: Section 2 describes the data and Section 3 estimates a benchmark model. The form of the possible spatial dependence is not clear from theory so we proceed cautiously, exploring the data in a fairly non-parametric way before specifying the form in a standard matching function format; Section 4 sets out our exploratory analysis of the spatial dependence. Section 5 presents the results of parameterising this in the standard specification of the matching function. Section 6 concludes.

2. Description of the Data

We analyse monthly gross worker flows at a local level, estimating matching functions for 303 TTWAs in the UK between October 1985 and December 1995[4]. The geographic entities were originally constructed through an algorithm which ensured that at the time of collecting the data a minimum of 75% of employed residents work within the district[5]. Therefore, while these areas do represent local labour markets, a significant minority of residents work in and so are connected to employment networks in neighbouring TTWAs.

Unemployment and vacancy stocks and flows are registration data provided by local employment agencies. Such administrative data has the advantage of being readily available on a regular basis, at high frequencies, and at a very disaggregate regional level. On the other hand, the data is necessarily based on the official definitions and counts of unemployment and vacancies, thus excluding for example people who would be counted as ILO-unemployed

[4] Labour market data is extracted from NOMIS at University of Durham.

[5] TTWAs were constructed based on commuting data from the 1981 Census. The observations for February 1986 are missing. Four travel-to-work areas (Fishguard, Pickering and Helmsley, Ripon, Thirsk) contain a value of zero for vacancy stocks and vacancy outflows for most of the sample period. Since it is not clear whether these zero observations are due to misreporting, or to a revision of district borders, we decide to delete these districts. Moreover islands (Orkney, Shetland, Western Isles) with the exception of Isle of White, which is close enough to the mainland, and Northern Ireland were not considered in our analysis.

but who are not eligible to claim benefits[6]. Moreover, registered vacancies only constitute one channel from which firms recruit personnel and job-seekers find employment. Gregg and Wadsworth (1996) report for Britain that about 70% of the unemployed, 30% of the employed and 50% of all employers use official Jobcentres as one of their search channels. Registered vacancies capture a disproportionate share of positions offered to low-skilled, manual workers as well as long-term unemployed, but on average account for only one third of total vacancies[7]. Furthermore, nothing can be said about the variation in non-registered vacancies across regions and over the business cycle. While Gregg and Wadsworth (1996) present evidence that the use of state employment services in Britain moves counter-cyclically, there is no evidence available on the spatial variation of search effort over the cycle.

We choose to model two flow variables: the outflow of unemployed and the outflow of filled vacancies. In most theoretical models these would be equal but as we shall see, they are in fact very different empirically. We do not think of these as two noisy measures of the same underlying variable, but rather take them to be different variables in theory: they measure different events. While in simple matching models they should be the same, because of employed job search, out-of-area hires, exits from the labour force and so on, there is no reason to expect them to behave the same empirically. Indeed, this allows us to look at the impact on the two sides of the labour market separately. The first variable we use is unemployment outflows in district i during period t: simply, the number of people leaving the unemployment register. Unemployment outflows have the clear drawback of including flows out of the labour force which can be expected to vary in size over the business cycle as well as across regions. Second, we use filled vacancies: vacancies notified in area i and filled during period t. Filled vacancies also include job finds due to activities of Career Offices, which mainly mediate school-leavers and labour market entrants (see Green, 1991)[8].

Figure 1 plots the aggregate totals for our data. Registered unemployment moves counter-cyclically and vacancies pro-cyclically. Research in recent years has investigated the cyclicality of the flows (see Antolin, 1995; Blanchard and Diamond, 1990; Burda and

[6] One factor which mitigates the discouraged worker bias in the registration data is pointed out by Schmitt and Wadsworth (1993). They find that, in contrast to common belief, workers who have lost eligibility for unemployment benefit search less intensively. Their explanation is that they are denied access to the training and counselling facilities of Jobcentres, underlining the important role of official employment agencies as a search channel in Britain.

[7] See Smith (1988), Green (1991), and Gregg and Wadsworth (1996).

[8] We also used data on job placings, which includes job seekers from i mediated to vacancies initially notified to other Jobcentres. However, the regression results proved to be very similar implying that either mediations to other regions closely match with vacancies filled by Career Centres, or are negligible in size.

Wyplosz, 1994). In our data, filled vacancies clearly move in a pro-cyclical manner, and unemployment outflows seem to move counter-cyclically. Appendix Table 1 provides summary statistics on the cross-sectional variation in the data. Average unemployment outflow rates suggest a mean duration of an unemployment spell just above six months, whereas the average duration of vacancies is only slightly above one month. We can disaggregate to examine TTWAs in five structural categories according to a region's degree of dependence on UK's principal urban centres (“metropolitan dominants”)[9]. Average unemployment outflow rates are lowest in metropolitan areas, particularly in London, which is, at least in part, due to the composition of the labour force with a larger proportion of high risk groups, *i.e.* the young and ethnic minorities. Appendix Table 2 shows the between-TTWA variance in the data and the within-TTWA variance. Unsurprisingly, the variance between TTWAs is much stronger than within TTWAs.

3. Estimating a Standard Matching Function

Typically, matching functions are not derived from some underlying modelling exercise, but are posited as a summary of the process matching workers and jobs. We follow that practice here.

Basic Specification

We consider a Cobb-Douglas specification of the matching function in log-linear form with fixed effects for time and districts,

$$\ln X_{it} = m_i + h_t + a \ln U_{it-1} + b \ln V_{it-1} + u_{it},$$

[9] Travel-to-work areas which were linked to the former by significant commuting ties, are labelled “metropolitan subdominants”. “Metropolitan rural areas” are also linked with commuting flows to one of the first two groups, but their main settlement falls below a certain threshold in size. Relatively independent areas are called “freestanding” and are divided in “urban” and “rural areas” according to the size of their main settlement. The classification is taken from a framework of local labour-market areas (LLMA) devised by the Centre for Urban and Regional Studies at Newcastle University to analyse urban and regional change (see Coombes and Openshaw, 1982). We match the 281 LLMAs with 310 TTWAs to transfer the classification. See also Champion (1994).

where X_{it} is the flow dependent variable in area i during month t; U_{it-1} and V_{it-1} are stocks of registered unemployed and vacancies in area i at the beginning of period t; m_i is a TTWA fixed effect controlling for regional characteristics, including the size of the TTWA; h_t is a time fixed effect controlling for aggregate shocks as well as seasonal fluctuations of worker-firm matches; and u_{it} is an error term for which the usual properties apply[10].

For all our results, we separately analyse two different flow variables: the number of unemployment outflows in the TTWA, and the number of vacancies filled through official Jobcentres (in the same TTWA). To avoid simultaneity bias, we date the unemployment and vacancy stocks at the beginning of the month (denoted *t-1*), while the flows occur during the month (denoted *t*)[11].

Recently two issues have been raised in the context of estimating matching functions: non-random matching and time aggregation bias. In the former, a sequential structure is imposed on the search process, with the assumption that once a contact between a firm and a worker does not result in a match, neither side includes this trading partner in the search pool again (see Coles and Smith, 1998). This implies a matching relationship between unemployment inflows and the stock of vacancies, and between the inflow of vacancies and the stock of unemployed. In the latter, Burdett *et al* (1994) show that time aggregation causes a (downward) bias in the matching parameters. Gregg and Petrongolo (1997) propose a solution to the time aggregation problem by transforming labour market stocks to include a fraction of contemporary inflows. In a longer version of this paper, available from the authors[12], we implement both these extensions to our model. We discuss these results briefly below.

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[10] An analysis of cross-sectional distributions of unemployment and vacancy outflow rates reveals considerable outlier problems in the data. In order to check whether our results are driven by these outliers, we replaced the three largest and smallest observations (for unemployment outflow and filled vacancy rates) for each TTWA with a missing value, which amounts to about 5% of the sample. The results did not change very much; only the estimates of spatial effects in Section 4 became somewhat more robust across specifications after trimming. The results presented are based on the full sample.

[11] Jobcentres count unfilled vacancies on the first Friday, whereas unemployment counts are on the second Thursday of each month. Therefore, when we use lagged unemployment in the *filled vacancy* regression, there exists a period of overlap of four to nine workdays, which may give rise to a simultaneity bias. This may potentially produce a downward in the estimated elasticity of filled vacancies with respect to the unemployment stock. No problem arises for the regressions with unemployment outflows as dependent variable.

Results

The results of estimating this basic matching function are in Table 1. We begin in column 1 by estimating simple OLS pooling over all districts between October 1985 and December 1995, restricting m_i and h_t to be constant across areas and time. This is therefore equivalent to the standard aggregate matching function now often estimated. We find positive and significant coefficients of unemployment and vacancy stocks as expected from the theory of job-matching. First, looking at unemployment outflows as the dependent variable, the coefficient on unemployment is 0.75, three to four times larger than that on vacancies. With filled vacancies as the dependent variable, the coefficient of vacancies is more than twice as high as the one on unemployment[13]. Returns to scale are close to one, but are statistically rejected in favour of decreasing returns.

Note, however, that this regression has no normalisation for the different size of the TTWAs. To account for this and other sources of structural heterogeneity, we allow for TTWA fixed effects in column 2 (we also include time effects). This changes the results significantly. With unemployment outflows as the dependent variable, the coefficients on log unemployment and vacancies are much lower, but remain positive and significant. With filled vacancies as the dependent variable, the coefficient on unemployment drops sharply and becomes negative. The importance of fixed effects shows that the results found in cross-sectional data by Coles and Smith (1996) may be a pure scale effect due to the size of travel-to-work areas[14]. The matching function clearly exhibits decreasing returns to scale.

A panel Durbin-Watson test for serial correlation and a likelihood ratio test for group-wise heteroscedasticity in columns 1 and 2 indicate the presence of non-spherical disturbances[15]. Therefore, in all subsequent regressions we apply a three-stage *GLS* procedure allowing for an AR(12) process and heteroscedasticity across TTWAs[16]. The results, shown in column 3, are similar to those in column 2, except that the unemployment coefficient in the filled vacancies equation now becomes positive.

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[12] Available from: http://www.ecn.bris.ac.uk
[13] This result closely resembles the findings of Coles and Smith (1996).
[14] See Münch, Svenjar and Terrell (1998) for a discussion of spurious scale effects in the estimation of matching functions with cross-section data.
[15] Moreover, a Breusch-Godfrey test also indicates the presence of higher order serial correlation.
[16] See Baltagi (1995). As column 3 indicates the estimation procedure removes serial correlation in residuals. However, heterscedasticity is still present. Calculating White's robust standard errors indicates that those are about 30% above ordinary standard errors. As the number of observations is large, and due to the fact that we only interpret coefficients at a 1% significance level, we only report ordinary standard errors.

We have also run a variety of other specifications, with results available from the authors. We have run versions allowing for non-random matching and time-aggregation bias. These support the role for an inflow-type variable, more strongly in the filled vacancy equation than the unemployment outflow equation, but produce results otherwise similar to those in the table. Adding flows as right-hand side variables yields a matching function that exhibits increasing returns to scale. We have run specifications without TTWA fixed effects, but with regional effects, TTWA structural variables and normalising with (annually interpolated) labour force data. The structural controls include dummies for dependence on a metropolitan centre, for whether a TTWA is situated on the coast and for the TTWA being crossed by a motorway. The results, available from the authors, are similar to Table 1 and so again are not reported here.

4. Spatial Spillovers

In this basic specification, we have ignored any spatial spillovers between TTWAs, but this assumption of independence of the observations of adjoining labour markets is invalid if such spillovers are present and may lead to bias (see Anselin, 1988 and Burda and Profit, 1996). Job-search activities of workers and recruiting activities of firms across district borders may influence the job-matching process in neighbouring regions. Although TTWAs in the UK were constructed to minimise commuting flows, search behaviour can clearly range more widely and hence interaction effects may constitute an important component of local job-matches. In this section of the paper, we look for evidence of spatial dependence, how this correlates with geographical distance and the business cycle.

An informal test for spatial effects in local labour markets is obtained by exploring the relation between the residual correlation from the matching function and road distances. We take a pair of TTWAs, compute the residual correlation from the matching function estimates (column 3 of Table 1), and correlate this with the road distance between main settlements within each of the TTWAs[17]. We do this separately for both our flow matching variables – unemployment outflows and filled vacancies. Figure 2 demonstrates that while road

[17] Road distances are measured to yield the fastest connection between the main settlements of two TTWAs, and calculated from the software Milemaster Home of the UK Automobile Association. Instead of filling all cells in the 303×303 distance weighting matrix, only pairs of TTWAs up to fifth order contiguity were taken into account. In the latter analysis, only external effects from TTWAs within 120 km were assumed to be relevant.

distances between districts only explain a small part of the residual correlation, they have a significant negative impact on residual correlation for both dependent variables. This distance decay effect is consistent with diminishing search intensities due to higher costs of job-search at longer distances. The regressions in Table 2 confirm this impression more formally. The dependent variable is the correlation between the residuals of two TTWAs; the number of observations is all possible pairs of TTWAs within 120km of each other. This correlation is regressed on the characteristics of that pair of TTWAs; that is: their distance apart, their order of contiguity, and regional fixed effects. The reported specifications were selected according to AIC. The residual correlation falls significantly as log distance increases, even after controlling for the degree of contiguity and a large set of regional dummies. Moreover, residual correlation declines with higher order contiguity. Fixed effects reveal a strong residual correlation among TTWAs in the London region, and high positive residual correlation between London TTWAs and those in the South East region. These suggest more strongly connected labour markets, possibly reflecting better transport infrastructure. For unemployment outflows, Table 2 indicates significant negative interaction effects between TTWAs from northern regions. Spatial correlation seems to be more pronounced with the residuals from the regression with unemployment outflows as the dependent variable.

A more formal way of testing for spatial dependence is to use Moran's *I* test (see Anselin and Hudak, 1992). This test is designed to detect spatial correlation from cross-section regression residuals. For our TTWA panel, we calculate the test statistic for each cross-section separately and analyse the resulting time series of tests. We do this separately for the residuals from each of our dependent variables; the residuals are taken from column 3 of Table 1.

The test statistic for each period t is constructed as

$$MI_t = \frac{u'Wu/w}{u'u/N} = \frac{u'Wu/u'u}{w/N},$$

where u is the vector of regression residuals and W is an $N \times N$ weight matrix with components w_{ij}, N is the number of TTWAs and w the sum of the weights. This test statistic simply produces a weighted covariance of the residuals, where the weights are based on the spatial properties of the observations, normalised by the unweighted covariance. Finally, the test statistic is then standardised to follow asymptotically a standard normal distribution (Anselin and Hudak, 1992).

We adopt two specifications for the weights – one discrete and one continuous. First, we simply use (0, 1) first-order contiguity dummies for each pair of TTWAs (equal to unity if two districts share a common border). Second, we use a function based on the road distance (D) between centres of the TTWAs, $w_{ij} = \exp(-hD_{ij})$. This allows a smooth decay of the effect with distance. Following Molho (1995), we pick h = 0.02; we did experiment with other values but no qualitatively different results were produced. The h parameter can be thought of as a discount factor in the spatial dimension. So a high degree of dependence among the residuals of neighbouring TTWAs will produce a high *MI* test score; a high degree of correlation among randomly scattered TTWAs will not.

Figure 3 plots the values of these standardised Moran's *I* statistics. We present results for both unemployment outflows and filled vacancies, and for both choices of weighting matrix. Left hand panels use the first-order contiguity weights, and right hand panels use the smooth distance decay weights. The figures clearly show that the null hypothesis of no spatial correlation is rejected at conventional significance levels for most periods and both dependent variables (since these are standardised, numbers above 2 may be considered significant). Along with Table 2, this test provides strong support for the importance of spatial spillovers in matching.

Figure 3 also yields another insight into the nature of these spillovers. The smooth lines plotted (12-month moving averages) provide evidence of cyclical variation in the spatial dependence. The intensity of spatial dependence for unemployment outflows moves counter-cyclically, and pro-cyclically for vacancy flows (even after controlling for the number of unemployed and vacancies in a local labour market). To confirm this more formally, we ran regressions of the Moran's *I* statistics shown in Figure 3 (the moving average using the smooth distance decay weights, transformed to quarterly observations to match with the GDP data) on a time trend, a lag and a cyclical indicator (GDP growth):[18]

Unemployment Outflows:

$$\underset{}{MI_t} = \underset{(3.93)}{2.750} + \underset{(1.06)}{0.017{*}time} + \underset{(8.41)}{0.607{*}MI_{t-1}} - \underset{(2.39)}{0.157{*}DlnGDP_{t-4}}$$

[18] Absolute t-values given in parentheses. Number of observations is 29, adjusted R^2 is 0.84 in the first regression and 0.79 in the second.

Filled Vacancies:

$$MI_t = \underset{(0.99)}{0.467} + \underset{(0.15)}{0.002 * time} + \underset{(8.21)}{0.806 * MI_{t-1}} + \underset{(1.98)}{0.107 * DlnGDP_{t-4}}$$

An increase in lagged real GDP by 1% depresses Moran's *I* statistic in the case of *unemployment outflows* by 0.16, whereas it increases by 0.11 in the case of *filled vacancies*. This seems to make sense: in good times, the unemployed lower their search radius, but employers are forced to increase theirs; in bad times, the unemployed have to search more widely, but firms can afford to search more locally.

Cyclical movements in spatial dependence could arise from a number of sources: variations in individual search effort, varying intensity of use of search and recruitment channels and compositional effects. First, spatial search costs and job finding probabilities will vary through booms and recessions, and induce different individual search efforts across regions. Second, given Gregg and Wadsworth's (1996) evidence on the cyclicality in the intensity of use of search channels, if different search channels have different geographical reach, an agent's choice of search channel also influences the spatial coverage of her search. Third, the composition of the pool of job seekers may not be invariant over the cycle: in economic downturns, labour shedding is more likely to affect all types of workers, whereas inflows into the unemployment pool during booms is more likely to be of a selective nature.

5. Estimation of Spatial Spillovers

We now investigate this spatial dependence more systematically. Burda and Profit (1996) present a stylised model of non-sequential job search, where job seekers optimise individual search intensities across local labour markets trading off expected benefit of job search against its costs. Both of these are assumed to depend on the distance between residence and target regions. Optimal search and recruiting intensities determine the relevant pools of participants in a local labour market. Plugging optimal search intensities into a generalised matching function which relates job matches to economic conditions everywhere, reveals that *(a)* changes in unemployment exit probabilities in a district *i* are linked to changes in local labour market conditions in any district *j* through a complex function of the effect on exit probabilities in all other districts. *(b)* both the size and the sign of external effects depend on a weighted sum of the impact on changes of exit probabilities in all other districts, where the weights are determined by a direct effect of the change of local labour market conditions elsewhere, plus an indirect effect which arises from changing search intensities in other districts.

Estimation of Augmented Matching Functions

We estimate a linear approximation of this augmented matching function:

$$\ln X_{it} = m_i + h_t + a \ln U_{it-1} + b \ln V_{it-1} + a^* \ln U^*_{it-1} + b^* \ln V^*_{it-1} + u_{it},$$

where U^*_{it-1} and V^*_{it-1} measure external effects of unemployment and vacancies in *foreign* travel-to-work areas. We specify the spatial spillover variables as a weighted sum of the unemployed and vacancies in neighbouring TTWAs, $U^*_{t-1} \equiv W\boldsymbol{U}_{t-1}$ *and* $V^*_{t-1} \equiv W\boldsymbol{V}_{t-1}$, where W is again a weight matrix based on the spatial properties of the data. We use the same two variants for W: a first order contiguity matrix (used in regressions (1) and (3)), and a smooth decay distance weighting matrix with $h = 0.02$ as above (in regressions (2) and (4))[19]. Both these choices weight nearer TTWAs more highly, as suggested by Burda and Profit (1996), as search costs rise at larger distances and search intensities diminish.

Table 3 shows the results of this estimation for our two dependent variables of unemployment outflows and filled vacancies. Taking unemployment outflows first, the elasticity with respect to 'local' unemployment and vacancies is positive and significant. In addition, we find a negative congestion effect of higher unemployment in 'foreign' TTWAs, which is robust across all specifications. This negative externality reflects strong competition from neighbouring TTWAs. This may in part be a composition effect: unemployed workers contacting a 'foreign' Jobcentre may exhibit a higher search intensity on average compared to the local unemployment pool. For vacancies, the externality is unambiguously positive and significant. Notably the elasticity is higher compared to the effect of a change of local vacancies. Even when accounting for spatial spillovers, the UK matching function clearly exhibits decreasing returns-to-scale. Recall that the dependent variable unemployment outflows includes flows to inactivity, so not all these exits are into jobs.

[19] In a longer version of this paper (see http://www.ecn.bris.ac.uk) we also allowed for non-uniform spatial dependence at varying distances by taking linear splines in distances between TTWAs.

Turning to the regressions for filled vacancies, we find a negative and significant elasticity with respect to local unemployment. However, standard matching theory results are recovered when spatial spill-over effects are taken into account: the positive externality of unemployed from other TTWAs indicates that UK Jobcentres are very successful in mediating local vacancies to job seekers from other districts, and that job seekers exhibit the flexibility to accept these jobs[20]. Another interpretation of the strong positive external effect of foreign unemployment is due to the fact that filled vacancies only count matches accruing from one search channel, *e.g.* official Jobcentres. Since local job seekers acquire information on the local labour market at lower costs, it seems reasonable to assume that the diversification of search channels is higher compared to job seekers from other regions, who will probably rely on the official employment service.

We have also run a variety of other specifications for these regressions. We have allowed for non-uniform dependence by using linear splines in the distance weighting matrix. As for the basic model in Table 1, we have run models allowing for non-random matching and time aggregation. We have also tried an alternative specification for all of these models (standard, non-random matching, time aggregation bias), using regional instead of TTWA fixed effects, the size of the TTWA (interpolated log labour force), and structural features such as proximity to metropolitan centres, accessibility (a dummy for a coastal location) and infrastructure (a dummy for being crossed by a motorway). These are all available from the authors. To summarise the results, we continue to find strong evidence in favour of spatial spillovers from neighbouring TTWAs. We also find different effects of the stocks and flows involved in estimating the non-random matching models.

Finally, we check for asymmetric spillovers between particularly high and low unemployment areas[21]. We construct the ratio of unemployment in the local TTWA (on the denominator) to the weighted average of its neighbours (the numerator). So a high value indicates a TTWA in which unemployment in neighbouring areas is much higher than locally. We then construct two dummy variables: one that picks out the TTWAs in the top 10% of the distribution of this and one picking out the bottom 10%. These are included in the regression alongside the basic spillover variables from Table 3 (we just run the version looking at contiguous TTWAs). The results are in Table 4. We find no asymmetry for

[20] It is important to remember that filled vacancies are defined as counting positions notified to a local employment service and filled with a job seeker referred to any Jobcentre or other agencies to whom it has copied the vacant position. Note, that while the coefficient of 'foreign' unemployment at smaller distances is only mildly significant in regression (6), it becomes larger and highly significant if we control for outliers in the data as described above.

TTWAs with particularly low ratios, but we do find effects from high ratio areas on filled vacancies. This implies that the spillover effect is significantly different in areas where 'foreign' unemployment is much higher than 'local' unemployment. Looking at 'foreign' unemployment the spatial effect becomes stronger, which means that unemployed in neighbouring TTWAs search more intensively if unemployment is much higher in their home TTWA. An alternative interpretation is that firms tend to recruit workers more intensively from areas with very high unemployment. Looking at 'foreign' vacancies the asymmetry shows that the spatial effect becomes weaker, since vacancies in neighbouring TTWAs with high unemployment are filled with local job seekers more rapidly.

6. Conclusions

Matching functions are widely used in labour economics and macroeconomics to summarise the job-filling and job-finding processes in labour markets. In this paper we have provided empirical evidence supporting this, showing that a strong relationship exists in the data between job formation, and unemployment and vacancies. We have used a long panel of local labour markets in Britain. We have also presented evidence on the nature of spatial externalities in a matching model. We find strong evidence of spill-over effects between local labour markets, including significant negative congestion effects in matching. For example, conditional on local conditions, high unemployment in neighbouring areas raises the number of local filled vacancies but lowers the local outflow from unemployment. A number of empirical puzzles[22] in this data remain for further investigation but overall, the results are supportive of the matching approach and show that one of the key matching function concepts, externalities, has empirical content.

These findings have implications for both macroeconomics and economic policy. For the former, our findings are indicative of significant spatial frictions underlying the matching function. The denial of instantaneous, frictionless trading is the basis of the search and matching approach. The role of externalities in matching is one important difference between that approach and standard price-taking assumptions. Such externalities are very difficult to isolate using macro data, so our results provide useful support of their importance. For economic policy, the spillover effects between neighbouring TTWAs imply that wider

[21] We are grateful to Dan Hamermesh for this idea.

consequences will follow any local unemployment shock. For example, a large business failure and consequent mass redundancies will raise unemployment locally; our findings show that this will also tend to depress neighbouring labour markets, reducing unemployment outflow rates there. Conversely, any policy reducing local unemployment will have wider benefits. This effect needs to be built into analysis evaluating the case for packages to 'rescue' large businesses.

[22] The different behaviour of the two dependent variables is a prime topic we wish to investigate.

Table 1. Regression Results: Matching function with time and TTWA fixed effects October 1985 - December 1995, 303 travel-to-work areas, 123 periods.

Explanatory variables (in logs)	**OLS**	**LSDV** *district and time fixed effects*	**GLS-DV** *district and time fixed effects, uniform AR(12) and groupwise heterosced.*
	1	2	3
Dep. Var. (logs): **Unemployment Outflows**			
Unemploy-ment, t-1	0.753*	0.633*	0.659*
	(0.002)	(0.004)	(0.005)
Vacancies, t-1	0.212*	0.071*	0.034*
	(0.002)	(0.002)	(0.002)
adj. Rsq.	0.9580	0.9902	0.9987
RTS	0.965*	0.708*	0.693*
	(976)	(3498)	(3335)
DW	1.221	1.291	1.959
LR (gr. Het.)	2839*	10618*	11121*
N	36663	36663	33633
Dep. Var. (logs): **Filled Vacancies**			
Unemploy-ment, t-1	0.314*	-0.042*	0.003
	(0.003)	(0.010)	(0.016)
Vacancies, t-1	0.653*	0.372*	0.389*
	(0.003)	(0.005)	(0.006)
Adj. Rsq.	0.8642	0.9359	0.9869
RTS	0.966*	0.330*	0.391*
	(270)	(2257)	(1089)
DW	0.840	1.171	1.961
LR (gr. Het.)	7901*	11964*	11917*
N	36663	36663	33634

Notes: Constant and fixed effects not reported. Standard errors in parentheses below coefficients. Due to the large number of observations, we only interpret coefficients at 1% significance, labelled with an asterisk. The number in parentheses below *RTS* gives the result of the T-test for *H0:CRTS*.

Table 2. Residual correlation and distance

Dependent variable: *Residual correlation of each pair of TTWAs following estimation of a matching function with dependent variable:*	log unemploy. outflows	log filled vacancies
log distance	-0.086 (7.29)	-0.040 (3.3)
1st order contiguity	0.551 (13.0)	0.213 (4.9)
2nd order contiguity	0.540 (11.0)	0.201 (3.9)
3rd order contiguity	0.532 (10.0)	0.179 (3.3)
4th order contiguity	0.532 (9.6)	0.186 (3.3)
5th order contiguity	0.513 (8.6)	0.168 (3.3)
Regional dummies:		
South East	0.145 (9.9)	0.099 (6.6)
East Anglia	-0.090 (4.6)	0.079 (3.9)
London	0.537 (2.4)	0.611 (2.6)
South West	-0.062 (5.4)	0.070 (6.0)
West Midlands	--	0.073 (4.2)
South East / East Anglia	--	-0.096 (3.9)
South East / London	0.215 (6.8)	0.188 (5.8)
South East / South West	--	0.136 (7.2)
South East / East Midlands	--	0.084 (2.8)
East Anglia / East Midlands	-0.097 (4.2)	0.106 (4.5)
South West / West Midlands	-0.125 (4.9)	--
West Midlands / East Midlands	-0.060 (3.6)	-0.114 (6.6)
West Midlands / Wales	-0.097 (4.7)	--
East Midlands / Yorks.& Humbers.	-0.050 (3.0)	--
East Midlands / North West	--	0.065 (2.3)
Yorks.& Humbers. / North West	0.091 (5.4)	--
Yorks.& Humbers. / Cumbria	-0.161 (2.7)	--
Yorks.& Humbers. / Northern	-0.116 (4.4)	--
North West / Cumbria	-0.138 (2.6)	--
North West / Wales	-0.104 (3.4)	--
Cumbria / Scotland	-0.114 (2.2)	--
Adj. R^2	0.120	0.072

Notes: The unit of observation here is a TTWA pair. The correlation between the residuals of the two TTWAs is the dependent variable, the residuals deriving from the estimation of a matching function with the variable named at the column head as the dependent variable. This correlation is regressed on characteristics of that pair of TTWAs, such as their distance apart, where in the country they are and so on. The distance cut-off is 120 km. The regional dummies (fixed effects) were constructed as follows: for all observations that contain correlations between TTWAs within region A (*e.g.* East Anglia), the dummy "region A" has the value of one, else zero. For all observations that contain correlations between TTWAs in region A and region B, the dummy "region A/region B" has the value of one, else zero. Only fixed effects for adjacent regions considered. The reported specifications were chosen according to an algorithm which maximises an AIC criterion. Absolute t-values in parentheses.

Table 3. Estimating Spatial Spillovers

With uniform AR(12) and groupwise heteroscedasticity. TTWA fixed effects and time dummies included.

Dependent variable	*log unemployment outflows*		*log filled vacancies*	
	(1)	*(2)*	*(3)*	*(4)*
Local TTWA variables				
log U_{t-1}	0.756*	0.777*	-0.074*	-0.077*
	(0.009)	(0.008)	(0.023)	(0.022)
log V_{t-1}	0.027*	0.025*	0.386*	0.384*
	(0.002)	(0.002)	(0.006)	(0.007)
Neighbouring TTWA variables				
(1) Contiguous TTWAs				
log $\Sigma\omega[c(1)]\times U_{t-1}$	-0.132*	--	0.143*	--
	(0.011)		(0.029)	
log $\Sigma\omega[c(1)]\times V_{t-1}$	0.039*	--	0.025	--
	(0.004)		(0.011)	
Neighbouring TTWA variables				
(2) Smooth distance decay				
log $\Sigma\omega[d]\times U_{t-1}$	--	-0.193*	--	0.205*
		(0.013)		(0.036)
log $\Sigma\omega[d]\times V_{t-1}$	--	0.081*	--	0.052*
		(0.006)		(0.018)
adj. Rsq.	0.9987	0.9988	0.9870	0.9871
RTS	0.690*	0.690*	0.480*	0.564*
	(1177)	(569)	(387)	(133)
DW	1.957	1.953	1.960	1.960
N	33633	33633	33633	33633

Notes: Neighbouring TTWA variables:
$\omega[c(1)]$ weights TTWAs which are contiguous (first order) as 1, and all others as 0.
$\omega[d]$ weights TTWAs by their distance from the focus unit, with weight $\exp(-\eta D)$, with $\eta = 0.02$.
See Table 1 and text for further explanation. Absolute standard errors in parentheses.

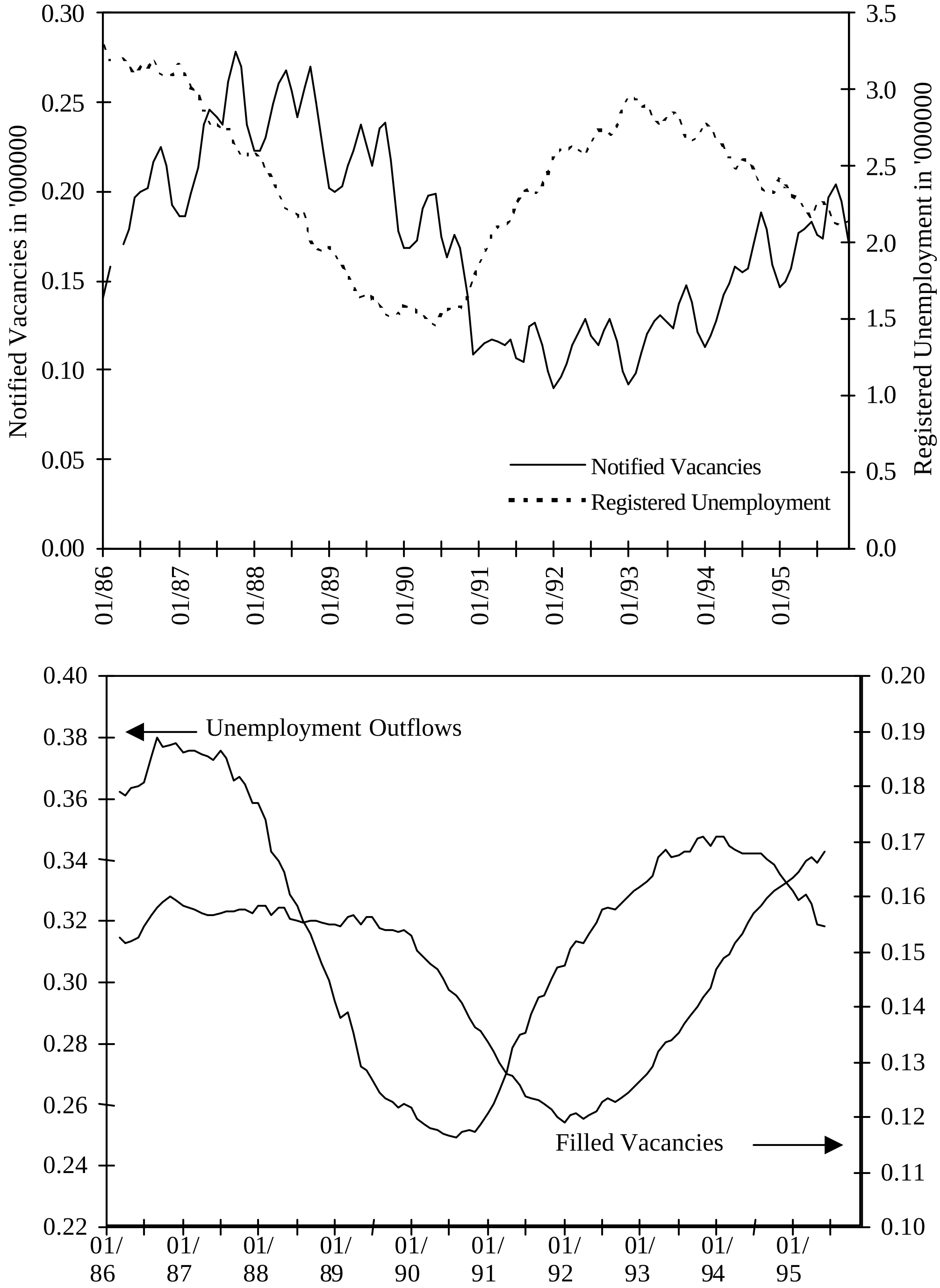
Table 4. Testing for Asymmetric Spatial effects

With uniform AR(12) and groupwise heteroscedasticity. TTWA fixed effects and time dummies included.

Dependent variable:	*log unemployment outflows*	*log filled vacancies*
Local TTWA variables		
log U_{t-1}	0.753* (0.009)	-0.093* (0.025)
log V_{t-1}	0.028* (0.002)	0.386* (0.006)
Neighbouring TTWA variables		
Overall spillover effect		
log $\Sigma\omega[c(1)]\times U_{t-1}$	-0.129* (0.011)	0.156* (0.031)
log $\Sigma\omega[c(1)]\times V_{t-1}$	0.039* (0.004)	0.030* (0.011)
Additional spillover effects from high unemployment ratio TTWAs		
log $\Sigma\omega[c(1)]\times U_{t-1}$	0.001 (0.004)	0.042* (0.010)
log $\Sigma\omega[c(1)]\times V_{t-1}$	-0.001 (0.005)	-0.057* (0.013)
Additional spillover effects from low unemployment ratio TTWAs		
log $\Sigma\omega[c(1)]\times U_{t-1}$	0.002 (0.004)	-0.007 (0.009)
log $\Sigma\omega[c(1)]\times V_{t-1}$	-0.001 (0.005)	0.007 (0.012)
adj. Rsq.	0.9988	0.9872
RTS	0.691* (1137)	0.464* (391)
DW	1.957	1.960
N	33633	33633

Notes: See Table 1. The asymmetry dummy was constructed as follows: for each TTWA we compute the ratio of its unemployment rate to the weighted average of the unemployment rates of its neighbours (defined by first order contiguity). We take the distribution of these and define a dummy variable for TTWAs with values in the highest 10% and a dummy for those in the lowest 10%. The variable therefore picks up TTWAs where the local unemployment is very different from the surrounding labour markets.

Figure 1. Registered Unemployment and Vacancies, Unemployment Outflows and Filled Vacancies.



* 12-month moving average, in '000 000

Figure 2a. Residual Correlation and Distance, Dependent Variable: Log **Unemployment Outflows**

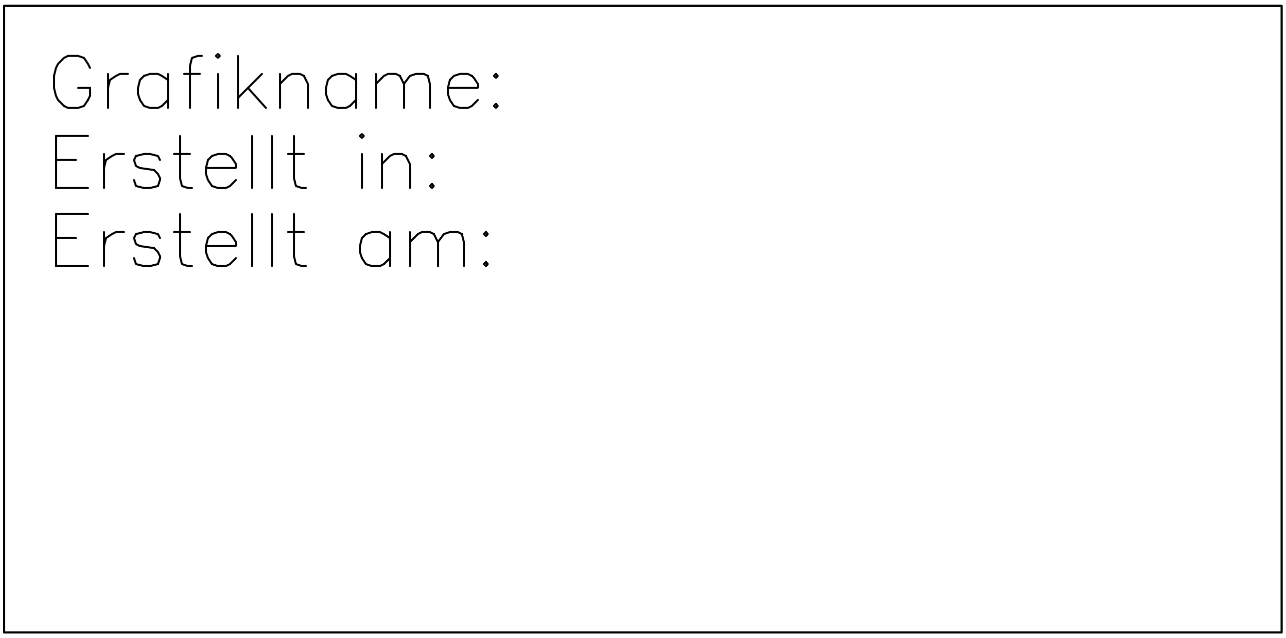


Figure 2b. Residual Correlation and Distance, Dependent Variable: Log **Filled Vacancies**

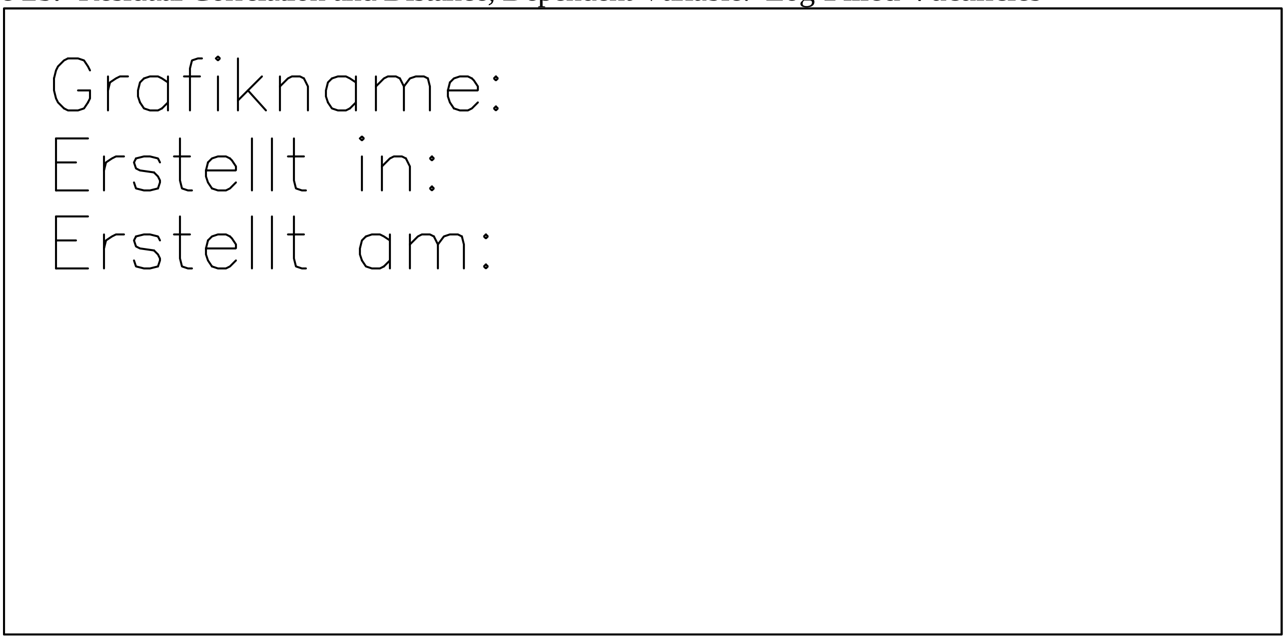


Figure 3a. Normalised Moran Statistics for Spatial Dependence (12-month moving averages).
Derived from matching function residuals
Dependent variable is log **Unemployment Outflows**

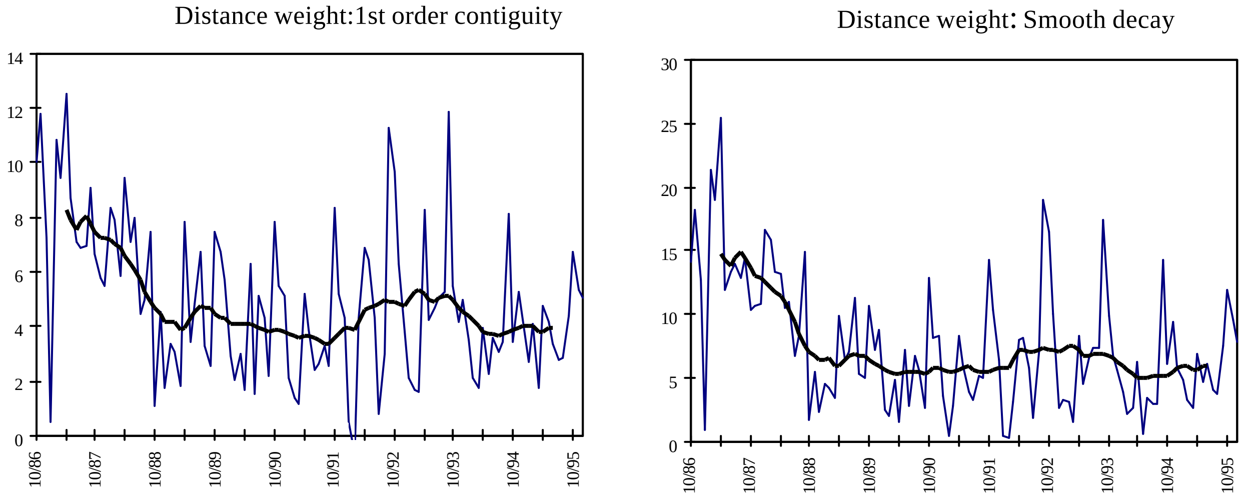
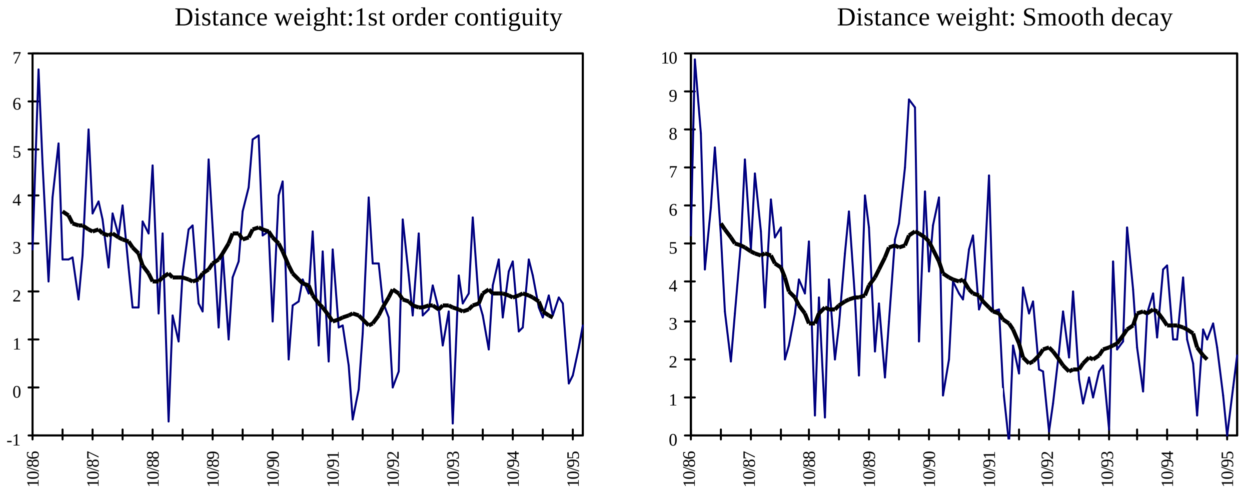


Figure 3b. Normalised Moran Statistics for Spatial Dependence (12-month moving averages).
Derived from matching function residuals
Dependent variable is log **Filled Vacancies**



Appendix

Table A1: **Means**
303 travel-to-work areas, Sept 1985-Dec 1995. By type of district and region

	Number of Observations	Unemployment Outflow rate	Filled Vacancy Rate	Unemployment Rate	Vacancy Rate
Overall	36663	0.161 (0.050)	0.928 (0.792)	0.103 (0.043)	0.010 (0.007)
Metropolitan dominant	3388	0.143	0.961	0.104	0.008
Metropolitan subdom't	7381	0.153	0.945	0.105	0.008
Metropolitan. rural	1573	0.171	0.939	0.091	0.010
Freestanding urban	18392	0.163	0.950	0.098	0.009
Freestanding rural	9075	0.168	0.945	0.108	0.012
South East	4719	0.172	0.704	0.083	0.0093
East Anglia	2299	0.173	0.971	0.083	0.0083
London	242	0.139	0.911	0.083	0.0068
South West	5808	0.169	0.945	0.100	0.0095
West Midlands	2662	0.151	0.940	0.090	0.0075
East Midlands	3267	0.160	1.014	0.095	0.0083
Yorks. & Humberside	2904	0.156	1.043	0.106	0.0066
North West	2420	0.155	1.238	0.106	0.0087
Cumbria	847	0.179	1.137	0.084	0.0113
Northern	1573	0.141	1.144	0.137	0.0074
Wales	3993	0.151	0.910	0.121	0.0132
Scotland	5029	0.158	0.919	0.120	0.0115

The flows are defined as the number leaving divided by the beginning of period stock, the unemployment and vacancy rates are defined as the number in the stock divided by the labour force (standard deviation in parenthesis).

Table A2: **Within and Between Variation**

Log unemployment outflows:	
- within variation	0.071
- between variation	1.334
Log vacancies filled:	
- within variation	0.161
- between variation	1.318
Log unemployment:	
- within variation	0.089
- between variation	1.521
Log vacancies:	
- within variation	0.176
- between variation	1.252

Note: Within variation defined as: $\Sigma\Sigma(x_{it}-\mathbf{x}_{i\bullet})^2/NT$, where $\mathbf{x}_{i\bullet}$ is the vector of TTWA means, and between variation defined as $\Sigma\Sigma(x_{it}-\mathbf{x}_{\bullet t})^2/NT$, where $\mathbf{x}_{\bullet t}$ is the vector of period means. N is the number of TTWAs and T the number of periods.

References

Anderson, P. and Burgess, S. (2000), 'Empirical Matching Functions: Estimation and Interpretation Using Disaggregate Data', Review of Economics and Statistics, vol. 82, no. 1, pp. 93-103.

Anselin, L. (1988), *Spatial Econometrics*: *Methods and Models*, Kluwer Academic Publications: Dordrecht.

Anselin, L. and Hudak, S. (1992), 'Spatial Econometrics in Practice: A Review of Software Options, Space and Applied Econometrics', Regional Science and Urban Economics, 22: pp. 509-536.

Antolin, P. (1995), 'Gross Worker Flows: How does the Spanish Evidence Fit the Stylised Facts?', Paper presented at the CEPR Workshop, 9/10 June in Berlin.

Baltagi, B.H. (1995), *Econometric Analysis of Panel Data*, John Wiley & Sons: Chichester.

Berman, E. (1997), 'Help Wanted, Job Needed: Estimates of a Matching Function from Employment Service Data', Journal of Labor Economics, 15: pp. S251-293.

Blanchard, O.J. and Diamond, P. (1989), 'The Beveridge Curve', Brookings Papers on Economic Activity, 1: pp. 1-60.

Blanchard, O.J. and Diamond, P. (1990), 'The Cyclical Behaviour of the Gross Flows of U.S. Workers', Brookings Papers on Economic Activity, 2: pp. 85-155.

Boeri T. and Burda, M.C. (1996), 'Active Labour Market Policies, Job Matching and the Czech Miracle', European Economic Review, 40: pp. 805-817.

Burda, M.C. and Profit, S. (1996), 'Matching Across Space: Evidence on Mobility in the Czech Republic', Labour Economics, 3: pp. 255-278.

Burda, M.C. and Wyplosz, C. (1994), 'Gross Workers and Job Flows in Europe', European Economic Review, 38: pp. 1316-1320.

Burdett, K., Coles, M. and van Ours, J. (1994), 'Temporal Aggregation Bias in Stock-Flow Models', CEPR Discussion Paper, No. 967.

Champion, A.G. (1994), 'Population Change and Migration in Britain since 1981: Evidence on Continuing Deconcentration', Environment and Planning A, 2: pp. 1501-1520.

Coles, M.G. and Smith, E. (1996), 'Cross-Section Estimation of the Matching Function: Evidence from England and Wales', Economica, 63: pp. 589-597.

Coles, M. G., and Smith, E. (1998), 'Market Places and Matching', International Economic Review, 39: pp. 239-255.

Coombes, M.G. and Openshaw, S. (1982), 'The Use and Definition of Travel-To-Work Areas in Great Britain: Some Comments', Regional Studies, 16: pp. 141-149

Fox, K.J. (1996).'Measuring Technical Progress in Matching Models of the Labour Market', Discussion Paper No. 7, University of New South Wales.

Green, A.E. (1991), 'Unemployment, Vacancies and Redundancies', in M. Healey (ed.), *Economic Activity and Land Use*: *the Changing Information Base for Local and Regional Studies*, pp. 43-65, Longman: Harlow.

Gregg, P. and Petrongolo, B (1997), 'Random or Non-Random Matching? Implications for the Use of the UV Curve as a Measure of the Matching Effectiveness', Discussion Paper No. 348, Centre for Economic Performance, London School of Economics.

Gregg, P., and Wadsworth, J. (1996), 'How Effective are State Employment Agencies? Jobcentre Use and Job Matching in Britain', Oxford Bulletin of Economics and Statistics, vol. 58, pp. 443-467.

Gross, D.M. (1997), 'Aggregate Job Matching and Returns to Scale in Germany', Economics Letters, 56: pp. 243-248.

Molho, I. (1995), 'Migrant Inertia, Accessibility and Local Unemployment', Economica, 62: pp. 123-132.

Mortensen, D.T. and Pissarides, C.A. (1999a), 'Job Reallocation, Employment Fluctuations and Unemployment', in J.B. Taylor and M. Woodford (eds.), *Handbook of Macroeconomics*, *Vol. 1B*, North Holland: Amsterdam.

Mortensen, D.T. and Pissarides, C.A. (1999b), 'New Developments in Models of Search in the Labor Market', in O.C. Ashenfelter and D. Card, (eds.), *Handbook of Labour Economics*, *Vol. 3B*, North Holland: Amsterdam.

Münich D., Svenjar, J. and Terrell, K. (1995), 'Regional and Skill Mismatch in the Czech and Slovak Republics', in OECD (ed), *The Regional Dimension of Unemployment in Transition Countries*, Paris.

Münich D., Svenjar, J. and Terrell, K. (1998), 'The Worker-firm Matching in Transition Economies: (Why) Are the Czechs More Successful than Others?', Working Paper No. 107, The William Davidson Institute.

Pissarides, C.A. (1986), 'Unemployment and Vacancies in Britain', Economic Policy, 3: pp. 499-540.

Schmitt, J. and Wadworth, J. (1993), 'Job Search Activity and Changing Unemployment Benefit Entitlement: Pseudo-Panel Estimates for Britain', Discussion Paper 148, Centre for Economic Performance, London School of Economics.

Smith, E. (1988), 'Vacancies and Recruitment in Great Britain', Employment Gazette, 96: pp. 211-213.

Warren, R. (1996), 'Returns to Scale in a Matching Model of the Labor Market', Economics Letters, 50: pp. 135-142.

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