Search Across Local Labour Markets

Christian Schluter and Panos Nanos

Local labour markets exhibit substantial and persistent differences in terms of unemployment rates, nominal and net-of-housing-cost wages, and firm productivities (see e.g. Moretti (2011), OECD (2005), Overman and Puga (2002)).

Governments spend considerable sums in place-based policies to combat such differences (e.g. Kline and Moretti (2013)).

Yet the spatial mobility of workers searching for jobs, unemployed and on-the-job, is limited and the population response to localised labour demand shocks is very slow (Amior and Manning (2016)).

Evidence for German Travel-to-work areas (TTWAs):

	Percentiles		
	10	50	90
mean unemployment rate	6.04	8.53	12.55
rel. house price index	0.59	0.74	0.87
mean daily log-wages	4.27	4.42	4.56
mean worker FEs	3.74	3.83	3.93
mean firm FEs	0.62	0.69	0.74
mean firm FEs (manufacturing)	0.73	0.79	0.84
mean firm FEs (services)	0.52	0.59	0.69

Notes: Period 2002-2008, spatial units are all 109 TTWAs in West Germany. TTWA means computed using weights given by district-level relative population size. Rows 3-7 based on LIAB.

Heterogeneity: The 90/10 ratio of local unemployment rates is 2.1, for relative house prices 1.5, and firm fixed effects 1.2.

This heterogeneity across local labour markets is not only pervasive but also **highly persistent**.

For instance, consider the year-to-year Spearman rank correlation of local unemployment rates.

- For all TTWAs, the smallest rank correlation is .968, for all districts it is .975.
- Even for a ten year lag, the rank correlation for all TTWAs is still .86.

Despite this persistent heterogeneity, the mobility of workers across local labour markets is small.

Who moves ?

Rupert and Wasmer (2012) using 2000 US Census data: 17% of employed and 25% of the unemployed have changed residence. 42% of relocations are across counties.

Calinedo et al. (2017): Yearly mobility rates in the US (3%) are approximately three times larger than the European average (1%).

In our German administrative data (LIAB), job-to-job transitions are of the same order of magnitude as out-of-job transitions.

Table: Spatial mobility and job transitions (LIAB 2002-08)

total $e \rightarrow u$ transitions	558,056	7.92%
total $u \rightarrow e$ transitions	547,823	7.77%
total $e \rightarrow e$ transitions	693,956	9.85%
total spells	7,046,710	
total relocations		
within TTWAs [%]	40.63	
across TTWAs [%]	59.37	
total relocations given transitions into employment $(u, e \rightarrow e)$		
within TTWAs [%]	72.70	
across TTWAs [%]	27.30	
total relocations given transitions into unemployment		
within TTWAs [%]	76.54	
across TTWAs [%]	23.46	

Why is spatial mobility so low ?

In order to address this empirical puzzle, we propose a new dynamic structural and empirical model of workers' job search across many local labour markets that integrates key concerns in urban and labour economics by focussing on spatial mobility and search frictions.

The model will be estimated using individual-level administrative data for Germany (LIAB).

The estimation then enables us to quantify, for instance, the cost of moving, and the impact of moving costs on local labour market outcomes.

We seek to quantify the barriers to mobility using new dynamic structural and empirical model of workers' job search across many local labour markets.

Workers search for employment opportunities within and across local labour markets. This job search is directed and unrestricted as both unemployed and employed workers can search.

Job seekers trade-off local differences in net salaries, unemployment probabilities and non-market aspects such as amenities.

Heterogeneity on the firm side arises from spatial differences in productivity.

The model is tractable as it does not rely on stationarity, unlike most random search models in the literature.

Each period is divided into five stages: births and deaths, separation, search, matching, and production.

The location of firms is taken as given. Production ($\pi(y, \mu) + z$) combines an aggregate component (y), a location specific component (μ) and a match-specific component (z).

The labour market is organised in a continuum of submarkets indexed by (x, k), where x is the lifetime utility offered by a firm to a worker, and k is the location of the submarket.

At the search stage, individuals can move and/or search for a job within or across locations. For instance, an employed worker in a match of productivity z in location l searches for a new job with probability λ_e, and looks for a match in a different location k with probability $\eta_e(z, l, k)$.

At the matching stage, individuals and vacancies searching in the same location and submarket meet.

The vacancy-to-searcher ratio is θ. The probability that a job-seeker meets a vacancy in this submarket is $p(\theta)$ and the probability that a vacancy meets a worker is $q(\theta) = p(\theta)/\theta$.

When a firm meets a job-seeker, nature draws z from the probability distribution $f(z)$.

As an example of how the model is formulated, consider a firm-worker pair in location l with match-specific productivity z.

At the beginning of the production stage, the joint value of this match $J_e(z,l,y)$ is given by the sum of the present discounted value of the worker's utility and the firm's profits.

The worker considers the net return from changing jobs (within and across locations)

$$\begin{aligned} D_e(J_e,z,l,k,y) &= \max_{x,\eta_e}\{(1-\eta_e)\left[p(\theta(x,l,l,y))(x-J_e(z,l,y))\right] \\ &+ \eta_e\left[p(\theta(x,l,k,y))(x-J_e(z,l,y)-c_e(l,k))\right]\} \end{aligned}$$

He picks the best location

$$D_e^{max}(J_e,z,l,y) = \max\{0, D_e(J_e,z,l,1,y),..,D_e(J_e,z,l,K,y)\}$$

resulting in the value function

$$\begin{aligned} J_e(z,l,y) &= \pi(y,\mu_l)+z+\beta(1-\tau)\mathbb{E}\max_{d_e}\{d_e J_u^{max}(l,\widehat{y}) \\ &+ (1-d_e)\left[J_e(z,l,\widehat{y})+\lambda_e D_e^{max}(J_e,z,l,\widehat{y})\right]\} \end{aligned}$$

Directedness of job search: A Worker self-selects into the submarket that maximises her expected gains from search, by trading off employment probabilities and the value of moving from their current position to a new job/location.

Unemployed/low value workers search in submarkets where the probability of entering is high and the gain is low, while high value workers search in submarkets where the probability of entering is low and the gain is high.

Firms in a submarket therefore know who they will meet and that their job offer will not be rejected.

Therefore, a firm's value from meeting a worker in a particular submarket is independent of the distribution of workers and so is the tightness in this submarket.

Since it is known that the non-spatial directed search model is identified, it follows that the location invariant parameters of the model are identified by within local labour market transitions between employment states.

Spatial variations then further aid this identification, and identify the location specific parameters such as those of the moving cost function.

Threats to identification arise from a lack of transitions since it is then difficult to disentangle low search probabilities from high moving costs. However, the richness of our model and the observed patterns of transitions rule out such observationally equivalent scenarios.

For instance, employment to employment transitions within the same locations inform about λ_e. Since moving costs between locations are invariant, but the expected benefit from moving is not, employment to employment transitions from location k to location l informs about the moving costs of the employed.

A similar reasoning applies to the unemployed who transit into employment across locations. If unemployed and employed transit from the same origin into the same destination, then the part of the moving cost related to employment status is identified.

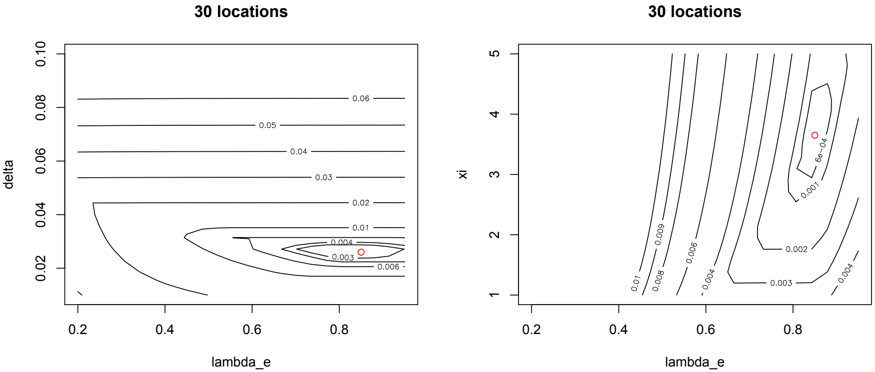
The policy functions of the model are not available in closed form. We consider the behaviour of the estimation objective function in the context of a simulation in order to provide a numerical illustration of identification.

We consider a simplified setting in which the only parameters to estimate are the frictional parameters (λ_e and δ), the vacancy posting cost ξ, and the coefficients of a moving cost function.

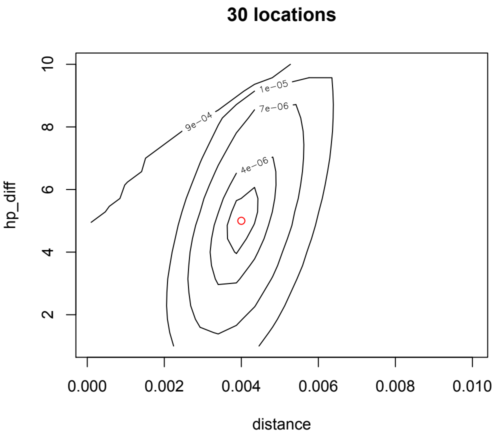
We set $c(l,k) = 1 + \alpha_1 \times \Delta hp(l,k) + \alpha_2 \times distance(l,k)$ where distance(l,k) measures the geographic distance between two locations, and $\Delta hp(l,k)$ is the difference between the relative house price indices.

We consider a model with 30 locations, which correspond to the 30 largest TTWAs in our German data.

A Numerical Identification Illustration



A Numerical Identification Illustration



The model is evaluated, for a given set of parameters, by value function iterations.

The parameters themselves are estimated by minimising the distance between a set of empirical moments of our transition data, and the corresponding simulated model-based moments.

In order to accommodate worker heterogeneity, we segment the labour market further by industry. Specifically, we consider manufacturing and services.

For a large number of locations the computations are time-consuming. The minimum distance criterion is therefore minimised using an evolutionary / genetic algorithm which is designed to locate the global minimum of the objective function relatively rapidly because computations are parallelised across processors.

Our implementation strategy focusses on the estimation of the (sector-specific) frictional parameters (δ, λ_e), the vacancy posting cost ξ, and the parameters of the moving cost function.

For simplicity, we fix all other parameters at plausible values. The discount factor (β), is .984, which corresponds to an annual discount rate of 5%. The elasticity of the matching function (γ) is .25, and similar to the value used in Shimer (2005). Home productivity (b) is .7, based on Hall and Milgrom's (2008)

Turning to the moving cost function, we take into account serveral factors. First, moving costs (monetary and psychological) might be a function of the physical distance between origin (l) and potential destination (k), which might also reflect the distinct regional identities and the federal structure of Germany.

Also taken into account are difference between housing costs.

Since there are potentially several factors that determine the relative attractiveness of a location (e.g. amenities), we include a set of destination dummies.

We also allow moving costs to differ by industry since the industrial composition of a place might contribute to its relative attractiveness. Since moving costs (psychological and direct) might differ between employed and unemployed, we also include an indicator for labour market status.

In summary, the moving cost function is for current location l and potential destination k:

$$c(l,k) = \left(\sum_{i \in \{sector\}} \alpha_i^s \times 1_{\{i=sector\}} \right) \times \left\{ \alpha^u \times 1_{\{u\}} + \alpha^d \times distance(l,k) + \sum_{j \in K} \alpha_j^{loc} \times 1_{\{j=l\}} \right\}$$

Table: Estimation and Model Fit

	Estimates		Model Fit				
	Manu.	Services	Moments	data	model		
λ_e	0.6232	0.7014	unemployment	2.522%	1.771%		
δ	0.0062	0.0181	relocations	0.047%	0.096%		
ξ	1.0972	3.0900		Manufacturing		Services	
α^s	1.6252	1.7195		data	model	data	model
			e $\rightarrow$ e transitions	1.71%	1.72%	4.09%	3.97%
			e $\rightarrow$ u transitions	0.8%	0.87%	1.93%	2.06%

Notes: Time unit is a quarter. Based on LIAB for years 2002-08.

Table: Counterfactual Experiments: Reducing moving costs

	Baseline	75% cost	25% cost	no cost
relocations	0.096%	0.230%	0.312%	3.019%
unemployment	1.771%	1.756%	1.699%	1.585%
Manufacturing				
e $\rightarrow$ e transitions	1.72%	1.72%	1.72%	1.72%
e $\rightarrow$ u transitions	0.87%	0.87%	0.87%	0.87%
Services				
e $\rightarrow$ e transitions	3.97%	4.12%	4.75%	7.79%
e $\rightarrow$ u transitions	2.06%	2.06%	2.06%	2.06%