Search Across Local Labour Markets*

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Abstract

Local labour markets exhibit substantial and persistent differences in terms of unemployment rates, nominal and net-of-housing-cost wages, as well as firm productivities. Yet the observed 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. 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. 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. The model is tractable as it does not rely on stationarity, unlike most random search models in the literature. In our empirical application, this model is estimated structurally using individual transition data obtained from an administrative employer-employee panel from Germany (LIAB). The model enables us to quantify the underlying drivers of and barriers (such as relocation costs, search frictions, and their amplifying interaction) to the spatial mobility of workers, and to investigate counterfactual scenarios such as place-based policy interventions proposed to promote spatial mobility.

Keywords: geographic mobility, internal migration, job search, search frictions, local labour markets

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1 Introduction

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 (e.g. Kennan and Walker (2011)) and the population response to localised labour demand shocks is very slow (Amior and Manning (2016)). We model the workers' search for jobs within and across local labour markets in order to quantify the underlying drivers of and barriers to the spatial mobility of workers. Mobility costs (the key mechanism in Kennan and Walker (2011)) and search frictions interact. Answering the questions of who searches when and where enables us to provide explanations for the persistence of spatial wage and unemployment differentials.

To address these important issues, we propose a new dynamic empirical model of directed spatial search and estimate it structurally using an administrative employee-employer panel for Germany. Building on the contributions of Shi (2009) and Menzio and Shi (2011), we extend the directed search paradigm by interpreting search spatially: job searchers (both the unemployed and on-the-job) search within and across local labour markets, trading off local differences in net salaries, unemployment probabilities and non-market aspects such as amenities in the face of moving costs. Our model thereby marries classic concerns in urban economics with the labour economics literature that emphasises the importance of search frictions.

We estimate this model structurally using individual transition data obtained from an administrative employer-employee panel from Germany (LIAB). This paper is, to the best of our knowledge, the first in which a directed search model is estimated on individual-level data rather than being calibrated using several aggregate data sources. The directed search paradigm is particularly appealing in our empirical setting, as more than 75% of contracts in Germany are governed by some form of collective agreement. Even for an as deregulated labour market as the US', Hall and Krueger (2010) document a substantial incidence of wage posting and searchers having a good idea as to what the considered job would pay.

Our modelling approach enables us to overcome several restrictions that leading contributions to the literature had to impose, relating foremost to the model's tractability, the group of searchers, and the number of spatial units.

1. The tractability of our directed search model (and the feasibility of our out-of-steady state analysis) follows from the self-selection of workers into local labour markets: workers only apply to jobs they intend to accept and firms only meet workers willing to fill their vacancies. Contact probabilities (and hence value functions) are therefore independent of the distributions of workers across states/locations. Random search, by contrast, usually does not permit such short-term analysis (an exception is Lise and Robin (2017), who consider, as we do, the joint surplus of a match), because firms can meet workers unwilling to accept their job offers so contact probabilities depend on the distributions of workers across states. Our approach thus complements the recent steady-state model of spatial random search of Schmutz and Sidibé (2016), which the authors

estimate using individual-level data for workers in French cities. Their model focuses on informational frictions, captured by higher job offer rates in the home location compared to alternative locations. Solving their model is challenging. Our directed search approach leads to much easier characterisations. Furthermore, considering firms and allowing for individual level heterogeneity, as we do, would further complicate the authors' approach.

2. Both unemployed and employed can search for new jobs in our model. This is in line with the data, as, for instance, Rupert and Wasmer (2012) have demonstrated that both groups are spatially mobile: using data from the 2000 US Census, they report that 17% of employed and 25% of the unemployed have changed residence, and that 42% of relocations are across counties. In our German administrative data, job-to-job transitions are of the same order of magnitude as out-of-job transitions. By contrast, the leading models in the literature restrict job search either to the employed or the unemployed (e.g. Beaudry et al. (2012)).

3. Our implementation accommodates a large number of locations. In our empirical application we consider all 109 travel-to-work areas (TTWAs) in West Germany, which, unlike administrative spatial units (such as municipalities or cities) reflect the spatial organisation of economic activity and the idea of a local labour market. Leading dynamic models in the literature often restrict attention to a very small number of locations (e.g. Gould (2007) has two locations corresponding to a rural and an urban area; Baum-Snow and Pavan (2012) consider three locations corresponding to small/medium/large cities). Kennan and Walker (2011) consider inter-state moves, but have to restrict the information available to each individual. They observe that "(i)deally, locations would be defined as local labour markets; (...) even if J is the number of States, the model is computationally infeasible" (p.216). Our tractable directed search paradigm allows us to overcome this challenge.

4. Our dynamic model builds on the dynamic migration model of Kennan and Walker (2011). In both cases, the dynamic perspective complements the classic static spatial equilibrium models in the tradition of Rosen (1979) and Roback (1982) (e.g. surveyed in Glaeser and Gottlieb (2009)). There, utility is equalised across locations by house prices for all workers, or, as in Moretti (2011), for the marginal worker. These static models focus on the long run. However, Amior and Manning (2016) convincingly demonstrate, using an error correction model, that the adjustment process takes time. Our model thus complements this modelling strategy by providing micro foundations and a short run perspective. In Kennan and Walker (2011), the observed low mobility of workers is rationalised by high moving costs. We add to this mechanism by considering search frictions, which, in turn, are amplified by moving costs.

The paper is organised as follows. Section 2 establishes stylised facts about the extent and persistence of spatial heterogeneity, as well as the limited mobility of workers based on our German data. These empirical features inform our model. The directed search model is described next. We start in Section 3 with a description of the environment within which agents interact. The workers' transitions within and across local labour markets by employment states are presented in Section 3.2, where we take as given the decisions of workers and firms. These decisions are presented for the decentralised economy in Section 4, while Appendix A presents in detail the Social Planner's Problem, characterises its solution, and demonstrates that the competitive equilibrium is also socially efficient. In Section 5, we describe our estimation strategy, discuss identification of our model's parameters, outline the parameterisation employed in our structural estimation, and present preliminary estimation results. The appendices provide further details and supplementary analyses.

2 Persistent Spatial Heterogeneity and Limited Mobility Across Local Labour Markets: Stylised Facts for Germany

We proceed to describe and quantify the persistent spatial heterogeneity across local labour markets and the associated limited spatial mobility of workers in the setting of our empirical application. Specifically, we have at our disposal individual-level administrative employee-employer data for Germany. Throughout, we will interpret the notion of a local labour market as a travel-to-work area (TTWA). These empirical observations set the scene for and inform our theoretical model presented in Section 3.

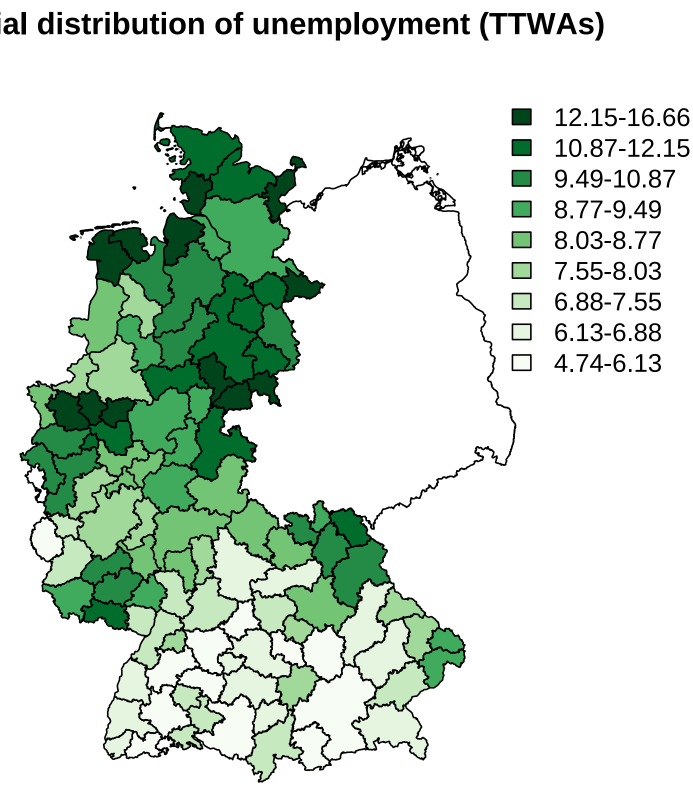
2.1 Data

Our individual-level transition data is drawn from a rich administrative employer-employee panel from the German Social Security system that has been assembled by the Research Data Centre (FDZ) of the German Federal Employment Agency into the LIAB data. The LIAB LM 9310 covers the years 1993 to 2010 (see Klosterhuber et al. (2013) for a recent description of the data, and Dustmann et al. (2009) for a recent use in the context of the German wage structure).

This dataset samples private sector workers and includes daily earnings and total days worked at each job in a year, the total length of unemployment spells, as well as information on occupation, industry and education. Since the data are based on administrative social security, individual information about labour market states and wage is of exceptional quality, and accurate to the day. While civil servants and the self-employed are not sampled, dependent private sector employees constitute about 80% of the workforce. The establishment identifiers link the workers employed in firms as of the 30th June to the annual waves of the IAB Establishment Panel. In each year, the data cover on average about 1.4 million individuals and 300,000 establishments.

We further enrich this data by merging in productivity estimates obtained by Card et al. (2013) in their study of establishment-specific wage premia. Specifically, using the methodology of Abowd, Kramarz and Margolis (1999), they estimate additive fixed effects for workers and establishments based on log wage regressions using the universe of German private sector workers (assembled in the Integrated Employment Biographies), from which our data is drawn. Following Card et al. (2013), we consider

Figure 1: Travel-to-work areas (TTWAs) and the spatial distribution of unemployment.



Notes: Depicted are 108 TTWAs in West Germany (we exclude Berlin), and mean local unemployment rates over time period 2002-2008, arranged into 9 quantile groups. The unemployment rate is obtained from www.regionalstatistik.de at the level of the district, and aggregated for TTWAs using weights given by district-level relative population size.

the time period 2002-2008. Our analysis focuses on prime-aged males (20-60) who reside in West Germany.

Our analysis of local labour markets is enabled by the spatial information contained in the LIAB. The data at our disposal provides information about the place of residence and the place of work. The spatial unit is the district (consistently coded with respect to its status on 31.12.2010), West-Germany being partitioned into about 326 districts. As these spatial units are defined administratively, they do not necessarily reflect the spatial organisation of economic activity and the idea of a local labour market. We therefore aggregate these administrative spatial units into travel-to-work areas using the classification of Eckey et al. (2006), which is based on a detailed factor analysis of actual commuting flows within radii of up to 60 minutes travel time.[1] Henceforth, we use the labels of travel-to-work areas (TTWA) and local labour markets interchangeably. This spatial aggregation of West German district results in 109 TTWAs, none of which is smaller than 50,000 inhabitants. We have excluded Berlin, given its special status as capital city and it being located in East Germany. The map of Figure 1 depicts these TTWAs. The federal constitutional and political structure of Germany also manifests itself in its urban structures, since Germany lacks a predominant center of gravity (such as Paris or London). Finally, in order to control for the spatial differences in the cost of housing and living, we also use a district-level house price index based on actual transactions recorded on the largest German online portal rendered comparable by hedonic price regressions.[2]

2.2 Data Descriptives: Persistent Spatial Heterogeneity, and Transitions

Table 1: Heterogeneity across all local labour markets

	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, the spatial units are 109 TTWAs. TTWA means computed using weights given by district-level relative population size. District-level data (population size) and mean unemployment rate obtained from www.regionalstatistik.de (Table 173-01-4 for year 2002, and Table 659-71-4 averaged over 2002-2008). House price index obtained from www.immobilienscout24.de, for year 2007, expressed relative to TTWA München. Worker and firm fixed effects (FEs) obtained from log wage regression described in Card et al. (2013), and averaged across the districts of each TTWA using establishment/district employment levels as weights.

We document the principal features of our data, first examining the evidence for persistent spatial heterogeneity across the all local labour markets, and then summarising the transition data. In order to provide greater detail and spatial resolution, in Data Appendix C, we consider explicitly 8 selected local labour markets.

Figure 1 depicts the spatial distribution of unemployment for 9 quantile groups. Southern Germany tends to have lower rates, while local unemployment in Lower

[1] We thank Reinhold Kosfeld for making this classification available to us.
[2] We thank www.immobilienscout24.de for making this index available to us.

Saxony and North Rhine-Westphalia is particulary elevated. It is clear that spatial heterogeneity is substantial. Table 1 reports the 10%/50%/90% deciles of the marginal distributions of unemployment, wages, relative house prices, as well as measures of productivity, i.e. firm and worker fixed effects. Since below we will segment the labour market by industry in order to accommodate further heterogeneity, we also report the firm fixed effects separately for manufacturing and services.

It is evident that spatial variations are pervasive. For instance, 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.

Table 2: Spatial mobility and job transitions.

total $e \to u$ transitions	558,056	7.92%
total $u \to e$ transitions	547,823	7.77%
total $e \to e$ 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 ($u, e \to e$)		
within TTWAs [%]	72.70	
across TTWAs [%]	27.30	
total relocations given transitions into unemployment		
within TTWAs [%]	76.54	
across TTWAs [%]	23.46	

Notes: Based on LIAB. We report the share of spells by type for the window 2002-2008.

Turning to the transition data, Table 2 reports measures of worker transitions on the labour market and across locations. The incidence of job-to-job transitions is of the same magnitude as out-of-job transitions, which we interpret as strong indirect evidence of the importance of on-the-job search. Our model accommodates both types of transitions, and both type of searchers are permitted to change location. Empirically, most job-related mobility is short range, as, given a labour status and location change, only about 25% change TTWA while three-quarters change location within their TTWA. All these data features inform our model, which is presented next.

3 A Tractable Equilibrium Model of Directed Search across Local Labour Markets

3.1 The Environment

Time is discrete and continues for ever. The economy is populated by a continuum of workers with measure 1. Each worker is endowed with an indivisible unit of labour and maximises the expected sum of periodical consumption discounted by the factor $\beta \in (0, 1)$.

Economic activity occurs within geographically defined markets or locations, indexed by $k \in K = \{1, ..., N(k)\}$ with $N(k) \geq 2$. Workers can move across locations, whereas firms cannot. Moving from source location l to a new destination location k is costly, and measured by a cost function $c_i(l, k) \geq 0$ that depends on the employment state of the individual i ($i \in \{u, e\}$). Hence we have ex ante heterogeneity of workers in terms of relocation costs; in our empirical application, we will introduce further sources of heterogeneity by segmenting the labour market by industry.

In addition to the endogenous mobility of workers, there are also exogenous relocations: every period a random sample of workers (employed or unemployed) leave the economy; for simplicity, these transitions are labelled as deaths. The "mortality rate" $\tau \in [0, 1)$ is exogenous. Deceased individuals are replaced by an equal measure of new-born workers. These new entrants are randomly allocated across locations, join the unemployment pool, and cannot search during their first period.

There is a continuum of firms with positive measure in every location k. Each firm uses a technology that turns one unit of labour into $\pi(y, \mu)+z$ units of output, where π is a constant returns to scale, increasing, and concave function. The first component of productivity, y, is common to all firms and its value lies in $Y = \{y_1, ..., y_{N(y)}\}$ with $N(y) \geq 2$. The second component of productivity, μ, is specific to the location of the firm $\mu \in \{\mu_1, ..., \mu_{N(k)}\}$. The third component of productivity, z, is specific to a firm-worker pair, and its value lies in $Z = \{z_1, ..., z_{N(z)}\}$ with $N(z) \geq 2$. The aggregate component of productivity y captures aggregate business cycle conditions, whereas μ captures local differences in productivity driven by e.g. agglomeration economies (as emphasised by e.g. Combes et al. (2012)). Hence our model exhibits ex ante heterogeneity on the side of the firm, since firms' productivities differ spatially (see also Kaas and Kircher (2015) on the importance of firm heterogeneity). Firms can enter freely a location, and inherit the common location-specific productivity component. In equlibrium, with free entry, firms will be indifferent in which location to produce since all firms will earn the same profits.

3.1.1 Timing

At the beginning of every period, the state of the economy can be summarised by $\psi = (y, u, g)$, where $y \in Y$ is the aggregate component of productivity, u denotes the measure of workers who are unemployed in the economy and is given by the sum of the measures of unemployed individuals in every location, $u = \sum_{k \in K}\{u_k\} \leq 1$ with $u_k \in [0, 1]$, and g is a function $g : Z \times K \to [0, 1]$ with $g(z, k)$ denoting the measure of workers who are employed in matches with idiosyncratic productivity z in location k. Every location k therefore consists of a collection of submarkets indexed by x.

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

At the separation stage, within each submarket x, and each location k matches between firms and workers are destroyed with probability $d_e(z,k) \in [\delta,1]$, where $\delta \in (0,1)$ denotes the probability that a match is destroyed for exogenous reasons. Separated workers must spend one period in unemployment before searching. The unemployment pool consists of individuals searching for a match (labelled unemployed job-searchers) and individuals who cannot search for one period (labelled unemployed non-searchers) either because they are new entrants or recently separated. At the separation stage, within each location k unemployed job-searchers become unemployed non-searchers with probability $d_u(k) \in [0,1]$. The measure of unemployed non-searchers in location k is denoted $ns_k \in [0,1]$, and the corresponding measure of unemployed job-searchers is given by $u_k - ns_k$.

At the search stage, individuals can move and/or search for a job within or across locations. Unemployed non-searchers move from their current location, l, to a different location, k with probability $\eta_m(l,k) \in [0,1]$. Unemployed job-searchers look for a job with probability $\lambda_u \in [0,1]$, while employed workers search with probability $\lambda_e \in [0,1]$. The probability that an unemployed individual in location l looks for a job in a different location, k, is $\eta_u(l,k) \in [0,1]$. Similarly, the probability that a worker employed in a match of productivity z in location l looks for a match in a different location, k, is $\eta_e(z,l,k) \in [0,1]$. At the search stage, firms decide how many vacancies to post. The cost of maintaining an open vacancy is $\xi > 0$ per period.

At the matching stage, individuals and vacancies searching in the same location and submarket meet. The meeting technology is constant returns to scale and can be expressed as a function of the submarket and location specific vacancy-to-searcher ratio, θ, i.e. the local labour market tightness. 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 in Menzio and Shi (2011), we allow for learning frictions. The firm-worker pair do not directly observe their match-specific productivity: they observe s, which is a signal of z. With probability $\alpha \in [0,1]$, the signal s is equal to z and with probability $(1-\alpha)$ the signal s is drawn from f independently of z. At opposite ends of the spectrum stand the cases of experience goods ($\alpha = 0$) and inspection goods ($\alpha = 1$). In the latter case, the quality of the match is known before forming it, in the former case no information is available. The informativeness of signals may differ across locations: $\alpha_{ll} \geq \alpha_{lk} \forall l,k \in K$.[3] Conditional on the signal, s, firms decide to hire the worker using a selection criterion r. A firm hires a worker if and only if the signal s about the quality of their match is greater than or equal to r. The probability that the signal about the quality of the match is above the selection cutoff r is given by $m(r) = \sum_{s \geq r} f(s)$.

At the production stage, an unemployed individual in location k, produces b_k units of output, where $b_k \in B = \{b_1, ..., b_{N(k)}\}$ and also enjoys flow utility A^u_k, where

[3] Kennan and Walker (2011) assume that workers only know the wage in their home location, and need to move to other locations to determine the local wage. Schmutz and Sidibé (2016) also assume the existence of informational frictions across locations.

$A_k^u \in A^u = \{A_1^u, ..., A_{N(k)}^u\}$, from local amenities. A worker employed in a match with idiosyncratic productivity z in location k produces $\pi(y, \mu_k) + z$ units of output and also enjoys flow utility A_k^e, where $A_k^e \in A^e = \{A_1^e, ..., A_{N(k)}^e\}$, from local amenities. After production, the firm-worker pair observe z. At the end of this stage, nature draws next period's aggregate component of productivity, $\widehat{y}$, from the probability distribution $\phi(\widehat{y}|y)$, where $\phi : Y \times Y \to [0, 1]$.

3.1.2 The Labour Market

The labour market is organised in a continuum of submarkets indexed by (x, r, k), where x is the lifetime utility offered by a firm to a worker, r is the selection criterion, and k is the location of the submarket. As is usual in this type of directed search model, employment contracts are assumed to be complete in the sense that a contract can specify the wage, w, the separation probability, d_e, the probability of search in a different location, η_e, and the submarket where the worker searches while on the job, (x, r, k), as functions of the history of the aggregate state of the economy and the quality of the match, z. The firm maximizes its profits by choosing the contingencies for d_e, η_e, x, and r so as to maximize the joint value of the match, and by choosing the contingencies for w so as to deliver the promised value x. The assumption of complete contracts captures the view that firms and workers have an incentive to find ways in practice to maximise the joint gains from trade.

3.2 Transitions within and across Local Labour Markets

We consider in detail the possible transitions that could be experienced by a worker in a particular employment state, location, and submarket since these are the principal objects of the empirical investigation. We then establish for each location l next period's measures of non-searchers $\widehat{ns}_l$, of unemployed job-seekers $\widehat{u}_l$, and of employed workers of productivity z, $\widehat{g}(z, l)$. These transitions are, of course, based on the optimal choices of workers and firms. In this section, we take these as given, and defer their derivations to Section 4. For notational simplicity, the optimal policy functions are indicated by the max superscript.

3.2.1 The Unemployed: Non-searchers and Job-seekers

At the beginning of the period, a measure τ of individuals (employed and unemployed) leave the economy while an equal measure of new entrants are equally distributed across locations (τ/K per location) and join the unemployment pool. New entrants are not allowed to search for a match (hence the label non-searchers ns), but are allowed to move to a different location.

Consider such a non-searchers in location l. These consist of non-searchers who have originated in location k' and have optimally moved to location l, and of non-searchers who have decided to stay in l. We denote the probability of the former event by $\eta_m^{max}(k', l)$, which equals 1 if the worker originating in location k' optimally chooses location l, and 0 otherwise. The staying probability is therefore $1 - \sum_{k' \neq l} \eta_m^{max}(l, k') \equiv 1 - \eta_m^{max}(l)$. Apart form these new entrants in l or k' who stayed in or moved to l, $\widehat{ns}_l$ includes: (a) individuals who entered the period as unemployed job-seekers in l or

k', decided to stop searching with source location-specific probability $d_u(l)$ or $d_u(k')$, and stayed in or moved to l; and (b) individuals who entered the period as employed job seekers in l or k', were separated with source location-specific probability $d_e(z,l)$ or $d_e(z,k')$, and stayed in or moved to l.

The measure of unemployed non-searchers in location l at the end of the search stage therefore equals

$$\begin{aligned}\widehat{ns}_l = & \frac{\tau}{N(k)}\left\{[1-\eta_m^{max}(l)] + \sum_{k'\in K}\eta_m^{max}(k',l)\right\} + (1-\tau)\times \\ & \left\{[1-\eta_m^{max}(l)]\left(d_u(l)\times u_l + \sum_{z\in Z}[d_e(z,l)g(z,l)]\right)\right. \\ & \left. + \sum_{k'\in K}\eta_m^{max}(k',l)\times\left(d_u(k')\times u_{k'} + \sum_{z\in Z}[d_e(z,k')g(z,k')]\right)\right\}\end{aligned} \tag{1}$$

Consider next an individual who enters the period unemployed in location l. This individual does not leave the economy with probability $1-\tau$, and enters the search stage as an unemployed job-searcher with probability $1-d_u(l)$. At the beginning of the search stage, the individual looks for potential matches in location l with probability $1-\eta_u^{max}(l)$. With complementary probability $\eta_u^{max}(l)$, she searches in a different location. At the matching stage, the unemployed job-seeker meets a firm with probability $\lambda_u\, p(\theta_u^{max}(l))$, and a match with idiosyncratic productivity $z=s$ is created with probability $h_u^{max}(s)[a+(1-a)f(s)]$, while a match with $z'\neq s$ is created with probability $h_u^{max}(s)(1-a)f(z')$. Therefore, at the production stage, the individual job-seeker is still unemployed with probability $1-\lambda_u\, p(\theta_u^{max}(l))\, m_u^{max}(l)$, where $m_u^{max}(l)=\sum_s[h_u^{max}(s,l)f(s)]$, while she is employed in a match of productivity z' with probability $\lambda_u\, p(\theta_u^{max}(l))\,[ah_u^{max}(z')+(1-a)m_u^{max}(l)]f(z')$.

Given these possible transitions, the measure of unemployed individuals in location l at the production stage $\widehat{u}_l$ includes the measure of unemployed non-searchers $\widehat{ns}_l$, and the measure of individuals who entered the period as unemployed job-seekers in location l, remained in the economy, searched for a job, but failed to find a match in l or in any other location k':

$$\widehat{u}_l = u_l\times(1-\tau)(1-d_u(l))\ \times[1-\lambda_u\, p(\theta_u^{max}(l))\, m_u^{max}(l)] + \widehat{ns}_l \tag{2}$$

3.2.2 Employed Workers

An individual who enters the period employed in a match of productivity z in location l reaches the search stage with probability $(1-\tau)(1-d_e(z,l))$. On-the-job searchers decide optimally where to locate at the beginning of the search stage. The worker searches in a different location with probability $\eta_e^{max}(z,l)$, and stays with probability $1-\eta_e^{max}(z,l)$. At the same time workers in matches of productivity $z'\neq z$ in other locations k decide to optimally relocate to l with probability $\eta_e^{max}(z',k',l)$, which equals 1 if this worker originating in location k' optimally chooses location l, and 0 otherwise.

At the matching stage, the worker meets a new firm with probability $\lambda_e\, p(\theta_e^{max}(z,l))$. A match of idiosyncratic productivity $z = s$ is created with probability $h_e^{max}(s,z,l)[a+(1-a)f(s)]$, while a match with productivity $z' \neq s$ is created with probability $h_e^{max}(s,z,l)(1-a)f(z')$. The worker stays in her original job with probability $1-\lambda_e\, p(\theta_e^{max}(z,l))\, m_e^{max}(z,l)$ where $m_e^{max}(z,l) = \sum_s [h_e^{max}(s,z,l)f(s)]$.

The production stage measure of individuals employed in matches of productivity z in location l, $\widehat{g}(z,l)$, therefore consists of workers who (a) entered the period employed in a match of productivity z in l and did not change employment status; or (b) entered the period employed in a match of productivity $z' \neq z$ in l or k' and found a match of productivity z in l; or (c) entered the period as unemployed job-seekers in l or k' and found a match of productivity z in l. Hence:

$$
\begin{aligned}
\widehat{g}(z,l) = \quad & (1-\tau) \times \Bigg\{ \quad g(z,l)[1-d_e(z,l)][1-\lambda_e\, p(\theta_e^{max}(z,l))\, m_e^{max}(z,l)] \\
& + \sum_{z' \in Z} \{\, g(z',l)[1-d_e(z',l)][1-\eta_e^{max}(z',l)]\lambda_e p(\theta_e^{max}(z',l)) \times \\
& \qquad [\alpha h_e^{max}(z,z',l) + (1-\alpha)m_e^{max}(z',l)]f(z)\} \\
& + \sum_{k' \in K} \sum_{z' \in Z} \{\, g(z',k')[1-d_e(z',k')]\eta_e^{max}(z',k',l)\ \lambda_e p(\theta_e^{max}(z',k',l)) \times \\
& \qquad [\alpha h_e^{max}(z,z',k') + (1-\alpha)m_e^{max}(z',k')]f(z)\} \\
& + u_l[1-d_u(l)][1-\eta_u^{max}(l)]\ \lambda_u p(\theta_u^{max}(l)) \times \\
& \qquad [\alpha h_u^{max}(z,l) + (1-\alpha)m_u^{max}(l)]f(z) \\
& + \sum_{k' \in K} \{u_{k'}[1-d_u(k')]\ \eta_m^{max}(k')\, \lambda_u p(\theta_u^{max}(k')) \times \\
& \qquad [\alpha h_u^{max}(z,k') + (1-\alpha)m_u^{max}(k')]f(z)\ \} \quad \Bigg\}
\end{aligned} \tag{3}
$$

4 The Decentralised Economy

We proceed to discuss the optimal search behaviour of workers in the decentralised economy, the optimal behaviour of firms, and the resulting equilibrium. Appendix A presents in detail the associated problem of the central social planner. In line with the earlier liteture on competitve and directed search, it will turn out that the decentralised equilibrium is socially efficient.

4.1 Value Functions

We proceed to consider in detail the value function of each worker by labour market status. The decision problem of where and in which submarket to search is broken down into two stages. In the first stage, a worker makes pairwise comparisons between the current location l and any possible destination k. In the second stage, the worker then picks the best alternative.

Consider an unemployed individual in location l at the beginning of the production stage. Her lifetime utility is denoted $U(l, y)$. In the current period, she produces b_l units of output and enjoys flow utility A_l^u from local amenities. With probability $(1 - \tau)$, she survives until the next period. At the separation stage, with probability $d_u(l, \widehat{y})$ she decides to quit to a state of non-searching, which gives her lifetime utility $J_u^{max}(l, \widehat{y})$, or to enter the search stage looking for a match. During the search stage, she decides where to search for a match by comparing the potential net gains from searching in each submarket within every location. The unemployed individual's choice of destination submarket and location is made optimally in two stages: first, she chooses the submarket within each location that maximises her value, and then selects the destination location that maximises the net gain from search. Suppose the optimally chosen destination submarket is x in location k. At the matching stage, she meets a vacancy that leads to an acceptable match giving her expected lifetime utility x with probability $p(\theta(x, r, l, k, \widehat{y}))m(l, k, r)$. If source and destination locations differ ($k \neq l$), the individual has to incur the moving cost $c_u(l, k)$. With probability $1 - p(\theta(x, r, l, k, \widehat{y}))m(l, k, r)$, she fails to meet an acceptable vacancy, so her employment status does not change and her expected lifetime utility is $U(l, \widehat{y})$. The unemployed job searcher's value is given by:

$$\begin{aligned} U(l, y) = b_l + A_l^u + \beta(1 - \tau)\mathbb{E} \max_{d_u}\{d_u J_u^{max}(l, \widehat{y}) \\ + (1 - d_u)[U(l, \widehat{y}) + \lambda_u D_u^{max}\left(U(l, \widehat{y}), l, \widehat{y}\right)]\}, \end{aligned} \tag{4}$$

where D_u^{max} is the total return to search function for unemployed job-searchers, giving the highest net gain from searching across all possible destination locations

$$D_u^{max}(U, l, y) = \max\{0, D_u(U, l, 1, y), D_u(U, l, 2, y), \ldots, D_u(U, l, K, y)\} \tag{5}$$

and D_u is the return to search function for unemployed job-searchers, giving the highest net return from searching across all possible submarkets within a destination location

$$\begin{aligned} D_u(U, l, k, y) = \max_{x, r, \eta_u}\{(1 - \eta_u)\left[p(\theta(x, r, l, l, y))m(l, l, r)(x - U)\right] \\ +\eta_u\left[p(\theta(x, r, l, k, y))m(l, k, r)(x - U - c_u(l, k))\right]\} \end{aligned} \tag{6}$$

Consider now an individual who became an unemployed non-searcher during the separation stage. At the beginning of the search stage, the unemployed non-searcher decides optimally whether to relocate and where. This choice is made optimally in two stages: first the unemployed non-searcher makes pairwise comparisons between her value in the current location l and her value in any possible destination location k net of moving costs, $J(l, k, y)$. In the second stage, she chooses the location k^* that gives her the highest net value, $J^{max}(l,) = J(l, k^*,)$. For the remainder of the period, the unemployed non-searcher is inactive in the labour market, engaging solely in home production, b_{k^*}. Hence, the problem solved by an unemployed non-searcher in location l is given by

$$J_u^{max}(l, y) = \max\{J_u(l, 1, y), J_u(l, 2, y), \ldots, J_u(l, K, y)\} \tag{7}$$

where

$$J_u(l,k,y) = \max_{\eta_m}\{(1-\eta_m)U(l,y) + \eta_m[U(k,y) - c_u(l,k)]\}. \tag{8}$$

Finally, 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, denoted $J_e(z,l,y)$, is given by the sum of the present discounted value of the worker's utility and the firm's profits. In the current period, the firm-worker pair produce $\pi(y,\mu_l)+z$ units of output, and the worker enjoys flow utility A_l^e from local amenities. With probability $(1-\tau)$, the worker survives until the next period. At the separation stage, with probability $d_e(z,l,\widehat{y})$ the match is destroyed: the worker joins the unemployment pool as a non-searcher with lifetime utility $J_u^{max}(l,\widehat{y})$, and the firm becomes idle with zero profit. With probability $(1-d_e(z,l,\widehat{y}))$ the match survives and the firm-worker pair enter the search stage. During the search stage, with probability λ_e, the worker searches for new matches: she decides where to search by comparing the potential net gains from searching in each submarket within every location. The worker's choice of destination submarket and location is made optimally in two stages: first, she chooses the submarket within each location that maximises the gain from search, and then selects the destination location that maximises the net gain from search.[4] Suppose the optimally chosen destination submarket is x in location k. At the matching stage, the worker meets a vacancy that leads to an acceptable match giving her expected lifetime utility x with probability $p(\theta(x,r,l,k,\widehat{y}))m(l,k,r)$. If source and destination locations differ ($k \neq l$), the worker has to incur the moving cost $c_e(l,k)$. With probability $1-p(\theta(x,r,l,k,\widehat{y}))m(l,k,r)$, the worker does not meet an acceptable vacancy, so she remains employed in a match of productivity z in location l with joint value $J_e(z,l,\widehat{y})$. The joint value of this match is given by:

$$\begin{aligned} J_e(z,l,y) = \pi(y,\mu_l) + z + A_l^e + \beta(1-\tau)\mathbb{E}\max_{d_e}\{&d_e J_u^{max}(l,\widehat{y}) \\ &+ (1-d_e)\left[J_e(z,l,\widehat{y}) + \lambda_e D_e^{max}\left(J_e,z,l,\widehat{y}\right)\right]\} \end{aligned} \tag{9}$$

where D_e^{max} is the total return to search function for employed job-searchers, giving the highest net gain from searching across all possible destination locations

$$D_e^{max}(J_e,z,l,y) = \max\{0, D_e(J_e,z,l,1,y), D_e(J_e,z,l,2,y), .., D_e(J_e,z,l,K,y)\} \tag{10}$$

and D_e is the return to search function for employed job-searchers, giving the highest net return from searching across all possible submarkets within a destination location

$$\begin{aligned} D_e(J_e,z,l,k,y) = &\max_{x,r,\eta_e}\{(1-\eta_e)\left[p(\theta(x,r,l,l,y))m(l,l,r)(x - J_e(z,l,y))\right] \\ &+\eta_e\left[p(\theta(x,r,l,k,y))m(l,k,r)(x - J_e(z,l,y) - c_e(l,k))\right]\} \end{aligned} \tag{11}$$

[4] Complete contracts imply that workers internalise the effect of their search decisions on the profits of the firm. Therefore, the solution to the search problem of employed workers should lead to a match that yields the maximum joint value net of search costs.

4.2 Vacancy Creation

The decision of firms to post vacancies in a submarket (x, k, r) is made optimally by weighing up the costs and benefits of vacancy creation at the margin. The cost of posting a vacancy is ξ. The expected benefit of posting a vacancy in submarket (x, k, r) is given by the product between the probability that the firm fills the vacancy, $q(\theta(x, r, l, y))$, and the value to the firm from filling the vacancy, $\sum_{s \geq r} \{(\alpha J_e(s, k, \widehat{y}) + (1 - \alpha)\mathbb{E}_z J_e(z, k, y) - x) f(s)\}$. A firm never creates a vacancy in any submarket where the cost of posting the vacancy ξ exceeds the expected benefit of matching with a worker. By contrast, if the expected benefit exceeds the cost of posting a vacancy, then the firm would seek to open as many vacancies as possible in that market. The free entry of firms guarantees that any profits are competed away, so submarket tightness, θ, is such that

$$\xi \geq q(\theta(x, r, k, y)) \sum_{s \geq r} \{(\alpha J_e(s, k, y) + (1 - \alpha)\mathbb{E}_z J_e(z, k, y) - x) f(s)\} \qquad (12)$$

and $\theta(x, r, k, y) \geq 0$ with complementary slackness. Condition (12) ensures that the market tightness function, θ is consistent with the incentives of firms to create vacancies.

4.3 Policy Functions

All policy functions reflect the two-stage optimisation strategy of workers. In particular, for unemployed job-searchers, the policy functions pertaining to the pairwise location comparison of stage one, given by equation (6), are $x_u(l, k, \widehat{y})$, $r_u(l, k, \widehat{y})$, $\eta_u(l, k, \widehat{y})$, and for the optimal location choice in stage two, given by equation (5), $x_u^{max}(l, \widehat{y})$, $r_u^{max}(l, \widehat{y})$, $\eta_u^{max}(l, \widehat{y})$. $d_u(l, \widehat{y})$ is the decision of unemployed job-searchers to quit to a state of non-searching and solves equation (4). Analogously, for unemployed non-searchers, we have the first stage policy function $\eta_m(l, k, \widehat{y})$, and the second stage policy function $\eta_m^{max}(l, \widehat{y})$. The policy functions for employed job-searchers follow the same logic: for the first stage we have $x_e(z, l, k, \widehat{y})$, $r_e(z, l, k, \widehat{y})$, $\eta_e(z, l, k, \widehat{y})$, for the second stage these are $x_e^{max}(z, l, \widehat{y})$, $r_e^{max}(z, l, \widehat{y})$, $\eta_e^{max}(z, l, \widehat{y})$. $d_e(z, l, \widehat{y})$ is the decision of the firm-worker pair to destroy the match. Finally, we observe that the policy functions can be expressed in terms of θ by solving (12): for the first stage problem we thus obtain $\theta_e(z, l, k, y)$ and $\theta_u(l, k, y)$, and for the second stage problem $\theta_e^{max}(z, l, y)$ and $\theta_u^{max}(l, y)$.

4.4 Equilibrium: Definition, Tractability and Efficiency

An equilibrium consists of a set of market tightness functions for unemployed job-searchers, $(\theta_u, \theta_u^{max})$, a set of market tightness functions for employed workers $(\theta_e, \theta_e^{max})$, a value function for unemployed non-searchers, J_u^{max}, a set of policy functions (η_m, η_m^{max}) for unemployed non-searchers, a value function for unemployed job-searchers, U, a set of policy functions for unemployed job-searchers, $(x_u(l, k, y)$, $r_u(l, k, y)$, $\eta_u(l, k, y)$, $x_u^{max}(l, y)$, $r_u^{max}(l, y)$, $\eta_u^{max}(l, y))$, a joint value function for firm-worker matches, J_e, and a set of policy functions for firm-worker matches, $(x_e(z, l, k, y)$, $r_e(z, l, k, y)$, $\eta_e(z, l, k, y)$, $x_e^{max}(z, l, y)$, $r_e^{max}(z, l, y)$, $\eta_e^{max}(z, l, y)$, $d_e(z, l, y))$. These functions satisfy the following conditions:

i. $(\theta_u(l,k,y),\ \theta_u^{max}(l,y))$ satisfy (12), (5), and (6);

ii. $(\theta_e(z,l,k,y),\ \theta_e^{max}(z,l,y))$ satisfy (12), (10), and (11);

iii. J_u^{max} satisfies (7) and (8), and $(\eta_m(l,k,y),\ \eta_m^{max}(l,y))$ are the associated policy functions;

iv. U satisfies (4), (5), and (6), and $(x_u(l,k,\widehat{y}),\ r_u(l,k,\widehat{y}),\ \eta_u(l,k,\widehat{y}),\ x_u^{max}(l,\widehat{y}),\ r_u^{max}(l,\widehat{y}),\ \eta_u^{max}(l,\widehat{y}),\ d_u(l,y))$ are the associated policy functions;

v. J_e satisfies (12), (10), and (11), and $(x_e(z,l,k,y), r_e(z,l,k,y), \eta_e(z,l,k,y), x_e^{max}(z,l,y), r_e^{max}(z,l,y),\ \eta_e^{max}(z,l,y),\ d_e(z,l,y))$ are the associated policy functions.

These conditions ensure that the strategies of each agent are optimal given the strategies of other agents.

In line with the earlier literature on competitive and directed (non-spatial) search we observe that the equilibrium agents' value functions and policy functions depend on the aggregate state of the economy only through aggregate productivity and not through the distribution of workers across employment states or locations. The equilibrium is therefore block recursive, and computations tractable. Furthermore, the decentralised equilibrium coincides with the solution of the social planner's problem, and is therefore socially efficient. Intuitively, these properties follow from the 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. In particular, by equation (12), 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.

We proceed to estimate structurally this search model using individual level data on transitions across labour market states and geographical transitions within and across local labour markets.

5 Empirical Implementation

5.1 Estimation Strategy

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. Specifically, collect all parameters to be estimated in a vector Θ, denote the i^{th} moment calculated from the data by $\widehat{m}_i$ and the corresponding model-simulated moment by $m_i(\Theta)$. The GMM criterion to be minimised is

$$GMM(\Theta) = \sum_i w_i \left(\frac{\widehat{m}_i - m_i(\Theta)}{\widehat{m}_i} \right)^2 \tag{13}$$

where w_i is a weight (set to unity currently, $w_i \equiv 1$). We take into account the local level of unemployment rates, the transition between labour markets states in each location (i.e. $e \to u$, $e \to e$, $u \to e$) as well as moving rates between any two locations. These moments are stated explicitly in Table B1 of Appendix B. Below, we report these rates in the results' tables after aggregation across all locations. In order to accommodate worker heterogeneity, we segment the labour market further by industry. Specifically, we consider manufacturing and services. Our computation and estimation strategy permits the frictional parameters (λ_e and δ), and the vacancy posting cost ξ to differ across industries, while the moving cost parameters are the same across all industries. 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. Computational details as well as validation experiments are collected in Appendix B.[5]

5.2 Identification

We discuss how transition data within and across labour market states and locations and their spatial variation, as well as the observed spatial variation in productivities and populations, identify the parameters of our model. Intuitively, 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. We make this argument more precise in what follows.

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. In particular, 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. For a set of potential locations that promise a similar lifetime utility x, a move from k to l rather than l' establishes an incomplete ranking of moving costs. Since moving costs are not a function of this lifetime utility x, more information about moving costs are gained if workers with different match specific productivities move from location k to location l, since the lowest match-specific component constrains the cost of this particular move. 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.

We exploit regional variation in the population of employed workers and regional variation in firm productivities within and across sectors to identify local amenities.

[5] The model is implemented and estimated in `Julia`. To illustrate the computational challenge, on a standard desk top computer, one evaluation of the objective function takes on average 6 minutes for the model of 30 locations.

We assume that amenities affect employed workers uniformly, so TTWAs with low firm productivity in a particular sector and a high share of workers employed in this sector should have higher amenities.

Turning to the location invariant cost of posting a vacancy ξ, the zero profit condition (12) implies that either the local submarket shuts down because the vacancy posting cost is too high, or that the local labour market tightness in the submarket adjusts by free entry of firms so that expected gains and the cost are equalised. Hence the number of local submarkets, and thus the total employment level informs about ξ. Higher local productivity implies more vacancies being created, and the spatial variation in local productivities further aids identification of ξ.

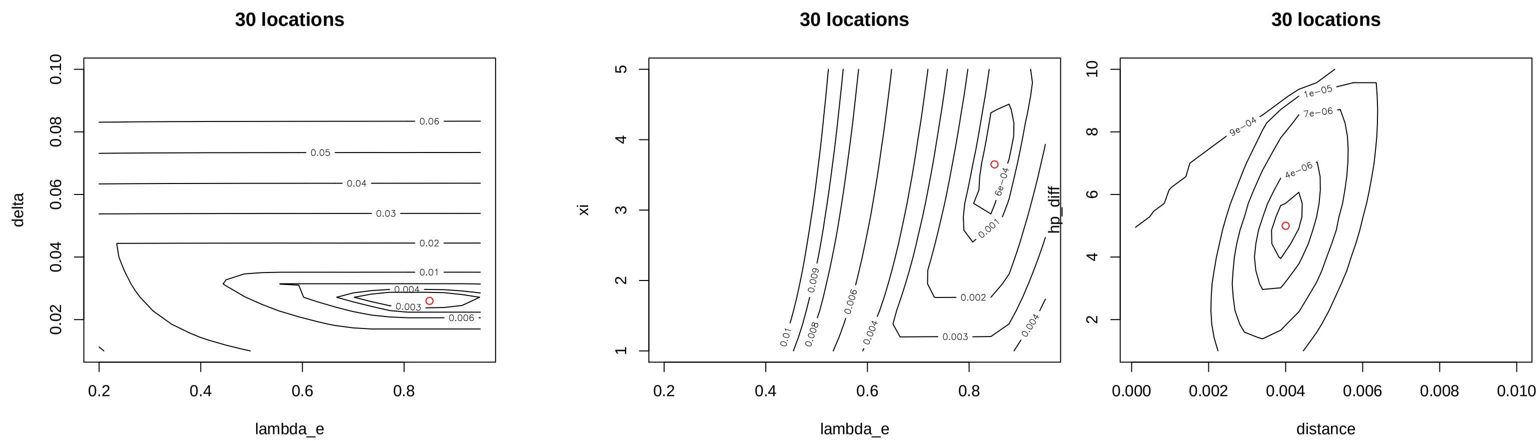
5.2.1 A Numerical Identification Illustration

Since the policy functions of the model are not available in closed form, it is impossible to obtain formal classic identification demonstrations. Instead, we follow the literature and consider the behaviour of the estimation objective function in the context of a simulation in order to provide a numerical illustration of identification.

The simulation design is as follows. The time period is a quarter. 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.[6] All other parameters are set as described in Section 5.3 below. Specifically, 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. The population parameters are set at $\lambda_e = 0.85$, $\delta = 0.026$, $\xi = 3.65$, $\alpha_1 = 5$, and $\alpha_2 = 0.004$. We consider a model with 30 locations, which correspond to the 30 largest TTWAs in our German data. The population model is simulated in order to compute the simulated empirical moments entering the estimation criterion. Figure 2 displays the contours of the minimum distance criterion for a range of candidate parameters while maintaining the remaining parameters at their population values. Also displayed are the population parameters (red circles). The controur plots suggest that the population values indeed minimise the estimation criterion; hence the examined model is identified.

[6] We also consider a more complicated setting where the model is estimated with amenities as discussed in 5.2 and implemented in 5.3. The results are similar to Figure 2 and available upon request.

Figure 2: 30 locations: Contour plot of the objective function.



(a) (b) (c)

Notes. Red circles: Population parameters, viz. $\lambda_e = 0.85$, $\delta = 0.026$, $\xi = 3.65$, $\alpha_1 = 5$ (difference between rel. house price index), and $\alpha_2 = 0.004$ (spatial distance).

5.3 Specifications

We proceeed to describe explicitly the specifications we have chosen to adopt in our implementation. As regards modelling the learning frictions, we consider explicitly here the inspection goods version of the model.

As regards the production function, we combine an aggregate component (y), a location-specific component (μ_l for location l), and a match-specific component (z). Location and match specific components are allowed to differ by industry. y follows a two-state Markov process with unconditional mean 1. z is given, as in Menzio and Shi (2011), by a discrete approximation of a Weibull distribution with mean μ_z, scale σ_z, and shape ν_z. Its dispersion is set as to reflect the global dispersion of the firm fixed effects. The location-specific component μ_l has been set to the rescaled deviation of the firm fixed effect (FFE) in that location for the specific industry from the overall mean, i.e. by industry $\mu_l = \beta_1 + \beta_2(FFE_l - F\bar{F}E)$ where $F\bar{F}E = K^{-1}\sum_l FFE_l$. We combine these 3 components using a production function given by $\pi(y, \mu_l) + z$, where $\pi = 2(0.5y^{1/2} + 0.5\mu_l^{1/2})^2$. Our production technology combines a CES production function and an additive match specific component, implying substitutability between the match specific component and the aggregate/location specific components, and, at the same time, some complementarity between the aggregate and the location specific components.

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. In particular, 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).

Amenities are assumed to be a summary measure of all pull factors that explain population distributions over and above the distributions implied by productivity differences. Specifically, we use the following parametric specification for amenities:

$$A_k^e = \alpha_1 + \alpha_2 \times Dec(pop, k) + \alpha_3 \times \sum_{i \in \{sector\}} [Dec(pop_i, k) - Dec(\mu_i, k)] \qquad (14)$$

where $Dec(pop, k)$ is the position of region k (i.e. the decile) in the distribution of employed workers across regions; similarly, $Dec(pop_i, k)$ is is the position of region k (i.e. the decile) in the distribution of sector i workers across regions.[7]

We assume that the flow utility from amenities in location k enjoyed by the unemployed, A_k^u, is a constant share of the corresponding flow utility enjoyed by employed workers, A_k^e, and that home productivity in this location, b_k, is also a constant share of average productivity across all sectors in this location. We set these constant shares at 50%, a proportion approximately equal to the average unemployment replacement rate in Germany between 2002 and 2008.[8]

Turning to the moving cost function, we take into account several factors. Moving costs (monetary and psychological) might be a function of the physical distance

[7]Diamond (2015) takes the complementary approach of enumerating explicitly specific dimensions of amenities. By contrast, Kennan and Walker (2011) capture amenities by estimating their model including fixed effects for different locations/regions.

[8]Source: DICE Database 2013.

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. In order to capture the idea that adjusting to life in a big city is more costly than settling in a smaller place, we also include an indicator for whether two TTWAs l and k include both one of the five largest German cities. We also allow moving costs to differ by segment since some groups may be more mobile than others. Since moving costs (psychological and direct) might differ between employed and unemployed, we also include an indicator for labour market status (a dummy equal to one if the individual is unemployed). In summary, the moving cost function is for current location l and potential destination k:

$$c(l,k) = \left(\alpha^u \times \mathbb{1}_{\{u\}} + 1\right) \times \left\{ \sum_{i \in \{segment\}} \alpha_i^s \times \mathbb{1}_{\{i=segment\}} + \alpha^c + \alpha^{bc} \times \mathbb{1}_{\{\text{big city}\}} + \alpha^{hp} \times \Delta hp(l,k) + \alpha^d \times distance(l,k) \right\} \tag{15}$$

The model is estimated by GMM using a sample that is constructed as follows: we partition the aggregate labour market into three segments/sectors, manufacturing, services, and financial services, and consider the 30 most populated travel-to-work-areas in West Germany (excluding Berlin). For our estimation, we use 330 moments: local unemployment (30 moments), relocations into each travel to work area (30 moments), local sector-specific job-to-job transitions (3 segments $\times$ 30 moments), local sector-specific job-to-unemployment transitions (3 segments $\times$ 30 moments), and local sector-specific employment shares (3 segments $\times$ 30 moments), see Table B1 for details.

5.4 Results (Preliminary)

Tables 3 and 4 report the results of our GMM estimation. Table 3 presents the sector-specific estimated model parameters for manufacturing, services, and financial services. Table 4 reports global (sector-invariant) and sector-specific moments aggregated across travel-to-work-areas. The model fits all sector specific data moments very well, indicating that our strategy of introducing heterogeneity by partitioning the labour market into three segments works. Our model-simulated global (non-sector specific) moments are also close to the corresponding data moments indicating that our model captures the main features of the aggregate labour market, and, more importantly, the relocation patterns observed in the data.

The sector-specific data moments suggest that the incidence of labour market transitions in the service sector is higher than in the manufacturing sector and similar in magnitude to financial services: both job-to-job transition and job separation rates in the service sector are approximately two times higher than the corresponding rates observed in the manufacturing sector; financial service workers experience as frequent job-to-job transitions as service workers, but experience job separations less frequently. This implies larger transition parameter estimates (λ_e, δ) in the service sector: our estimated sector-specific parameters, reported in Table 3, are indeed larger in services than in manufacturing and in financial services. Vacancy costs are estimated to be lower in the service sector than in manufacturing and financial services (approximately 1/3 of manufacturing costs), as one would expect. Finally, the estimated sector specific parameters of the cost function suggest that moving costs are highest for workers in the service sector and lowest in the manufacturing sector.

Table 4 reports that our model fits the data well by comparing global and sector-specific moments aggregated across travel-to-work areas. To illustrate how well our model performs in matching spatial heterogeneity in the data, we present Figures (3) and (4), which demonstrate that our model describes the spatial variation of employment in the aggregate (across sectors) and for the depicted sector of financial services. Our model's performance in matching spatial heterogeneity in employment in the different sectors is further evidenced by the high Spearman rank correlations between data- and model-computed local employment shares: 0.61 in manufacturing, 0.58 in services, and 0.72 in financial services.

Table 3: Sector Specific Parameter Estimates

	Manufacturing	Services	Fin. Services
ξ	4.7263	1.6324	4.5719
δ	0.0088	0.0176	0.0128
λ_e	0.5251	0.7919	0.4042
α^s	4.0515	6.3535	5.5105

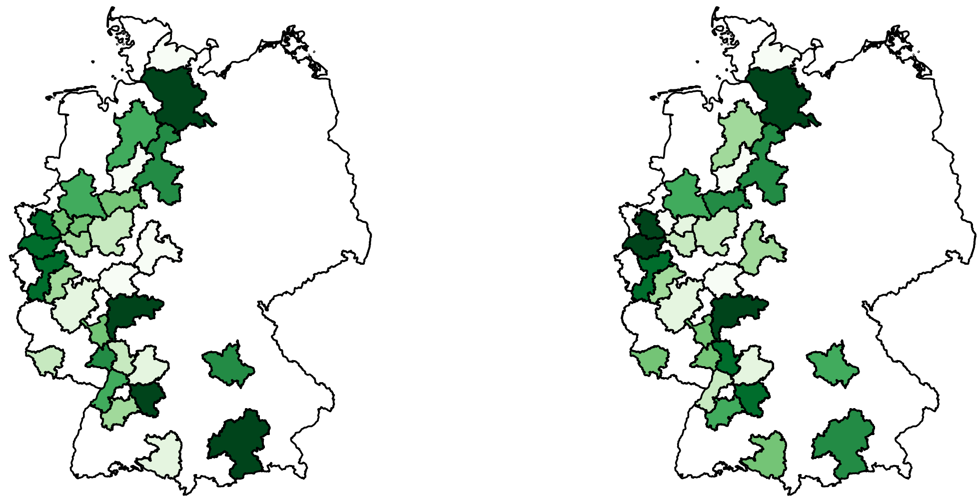
Notes: Time unit is a quarter. Based on LIAB for years 2002-08. Estimation by GMM, using $11 \times K = 330$ moments (where $K = 30$ denotes locations). The GMM criterion (13) is minimised by our evolutionary algorithm (see Appendix B.2).

Table 4: Model Fit

	data	model				
unemployment	2.760%	1.850%				
relocations	0.336%	0.329%				
	Manufacturing		Services		Fin Services	
	data	model	data	model	data	model
e $\rightarrow$ e transitions	2.14%	1.74%	4.83%	3.20%	3.13%	4.15%
e $\rightarrow$ u transitions	1.06%	1.10%	2.22%	1.91%	1.30%	1.50%

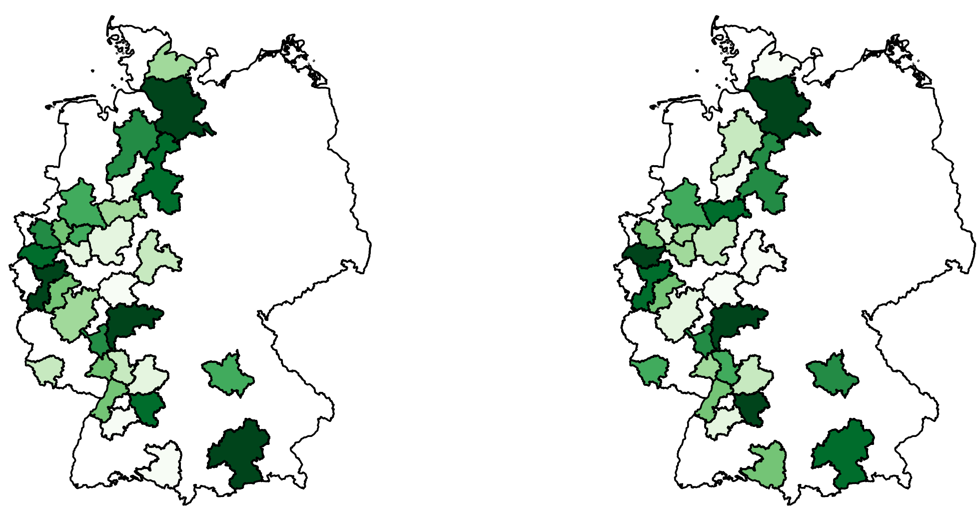
Notes: Time unit is a quarter. Based on LIAB for years 2002-08. Estimation by GMM, using $11 \times K = 330$ moments (where $K = 30$ denotes locations), to estimate $8 + 4 \times S = 20$ parameters (where $S = 3$ denotes sectors). Specifically, the global (non-sector specific) estimated parameters in the amenities and moving cost functions are: $\alpha_1 - \alpha_3$ from (14) and α^c, α^{bc}, α^{hp}, α^d, α^u from (15); the remaining twelve sector-specific parameters are presented in Table 3. The GMM criterion (13) is minimised by our evolutionary algorithm (see Appendix B.2).

Figure 3: Employment across 30 locations



Notes: Local employment in manufacturing, services, and financial services in the LIAB data (left) and in the model (right), arranged into 9 quantile groups. Using LIAB 2005 data and model generated data, we express the population of employed workers in these three sectors in every TTWA as a share of the population of all workers employed in these sectors across the 30 TTWAs.

Figure 4: Employment in Financial Services



Notes: Local employment in the financial service sector in the LIAB data (left) and in the model (right), arranged into 9 quantile groups.

5.5 Counterfactual Experiments (Preliminary)

In Section 5.5.1, we show how a reduction in moving costs can affect worker mobility. Further experiments are in progress.

5.5.1 Reducing Moving Costs

To illustrate how our model can provide useful insights into the motivations of workers to move across local labour markets, we conduct a counterfactual experiment: using our estimated model parameters, see Table 3, and the corresponding moments, see Table 4, as a benchmark, we gradually decrease moving costs and recalculate the global (sector-invariant) and sector specific moments. The results are reported in Table 5.

A decrease in moving costs by 25% increases relocations by a factor of 1.6. Decreasing moving costs by 75%, further increases relocations. In both cases, unemployment falls in response to these changes, but the decrease is small. Setting moving costs to zero makes relocations shoot up to 3.7% of total spells, suggesting that even moderate moving costs play a significant role in the allocation of workers across local labour markets. The effect of zero moving costs on unemployment is not significant, suggesting that lower moving costs lead to a re-allocation of workers across TTWAs: workers are more likely to move to high-productivity TTWAs even if job-queue lengths are longer.

An important observation is the sectoral heterogeneity in the responses to lower moving costs, captured entirely by varying job-to-job transition rates; job separations are almost unaffected by moving costs. The financial service sector exhibits the highest sensitivity to changes in moving costs: job-to-job transitions increase even for a modest decrease in moving costs (25%) and almost triple in magnitude relative to the baseline when moving costs are removed entirely. In the service sector, job-to-job transitions respond only to sizeable decreases in moving costs (75%) and more than triple relative to the baseline if moving costs are eliminated. Finally, the manufacturing sector exhibits the lowest sensitivity to moving costs: job-to-job transition rates remain almost unaltered until moving costs are set to zero.

Table 5: Counterfactual Experiments: Reducing moving costs

	Baseline	75% cost	25% cost	no cost
relocations	0.329%	0.510%	0.674%	3.659%
unemployment	1.850%	1.826%	1.769%	1.651%
Manufacturing				
e $\rightarrow$ e transitions	1.74%	1.75%	1.86%	5.65%
e $\rightarrow$ u transitions	1.10%	1.10%	1.07%	1.12%
Services				
e $\rightarrow$ e transitions	3.20%	3.21%	5.06%	10.15%
e $\rightarrow$ u transitions	1.91%	1.90%	1.93%	1.96%
Financial Services				
e $\rightarrow$ e transitions	4.15%	4.71%	7.12%	12.31%
e $\rightarrow$ u transitions	1.50%	1.50%	1.51%	1.48%

6 Conclusion

We have built a general equilibrium model of directed search on-the-job, where workers are allowed to search within and across regional labour markets that differ in terms of firms' productivities. Workers' job search yields an equilibrium characterised by a spatial distribution of wages and unemployment, and rich dynamics as workers experience transitions between different labour market states and between regional labour markets.

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Appendices

The structure of this Appendix is as follows:

- Appendix A presents in detail the Social Planner's Problem. We state the Planner's value function, and demonstrate that it can be decomposed into a set of smaller problems, labelled the component value functions. We then characterise the solution to the Planner's problem that enables us to establish who moves, when and where.
- In Appendix B we provide details of our estimation algorithm and report the results of a validation exercise.
- In Data Appendix C, we illustrate in some greater detail the heterogeneity among local labour markets and the geographic mobility among them by focussing on 8 selected travel-to-work areas.

A The Social Planner's Problem

At the beginning of every period, the social planner observes the aggregate state of the economy $\psi = (y, u, g)$. Births and deaths occur exogenously. At the separation stage, the planner chooses the probability $d_e(z, l)$ of destroying a match with productivity z in location l, $Z \times K \to [\delta, 1]$, and the probability $d_u(l)$ with which an unemployed job-searcher in location l stops searching for a job, $K \to [0, 1]$.

The social planner takes decisions in two steps. In the first step, the planner makes pairwise comparisons between an individual's current value in her location/employment state/submarket and her value in all possible destination locations/employment states/submarkets. In the second step, the planner chooses the destination location/employment state/submarket that maximises the individual's value. To maintain notational transparency, we denote the policy function chosen by the planner in the second step using a *max* superscript. Therefore, at the search stage, the social planner makes the following choices in two steps:

- the planner chooses the probability with which an unemployed non-searcher in l would relocate to any possible destination location $k \in K$, $\eta_m(l, k)$: $K \times K \to [0, 1]$; given this set of choices, the planner chooses the probability that an unemployed non-searcher in location l moves to a different location, $\eta_m^{max}(l)$: $K \to [0, 1]$;
- the planner chooses the probability with which an unemployed job-seeker in location l would search for a job in any possible destination location $k \in K$, $\eta_u(l, k)$: $K \times K \to [0, 1]$; given this set of choices, the planner chooses the probability that an unemployed job-seeker in l searches in a different location, $\eta_u^{max}(l)$: $K \to [0, 1]$;
- the planner chooses the probability with which a job-seeker currently employed in a match of productivity z in location l, would search for a job in any possible destination location $k \in K$, $\eta_e(z, l, k)$: $Z \times K \times K \to [0, 1]$; given this set of choices, the planner chooses the probability that a worker in a match with productivity z in location l searches for a job in a different location, $\eta_e^{max}(z, l)$: $Z \times K \to [0, 1]$;
- for unemployed job-seekers in location l, the planner chooses the tightness at any possible destination submarket $k \in K$, $\theta_u(l, k)$: $K \times K \to \mathbb{R}_+$; given this set of choices, the planner chooses the tightness at the submarket where unemployed job-seekers in l look for a match, $\theta_u^{max}(l)$: $K \to \mathbb{R}_+$;
- for job-seekers employed in matches of productivity z in location l, the planner chooses the tightness at any possible destination submarket $k \in K$, $\theta_e(z, l, k)$: $Z \times K \times K \to \mathbb{R}_+$; given this set of choices, the planner chooses the tightness at the submarket where workers employed in matches of productivity z in location l search for a job, $\theta_e^{max}(z, l)$: $Z \times K \to \mathbb{R}_+$.

At the matching stage, the social planner makes the following choices in two steps:

- the planner chooses the probability with which a meeting between an unemployed job-seeker in location l and a firm in any possible destination location $k \in K$ is turned into a match, given the signal s, $h_u(s, l, k)$: $Z \times K \times K \to [0, 1]$; given this set of choices, the planner chooses the probability that an unemployed job-seeker in l will match with a firm conditional on s, $h_u^{max}(s, l)$: $Z \times K \to [0, 1]$;

- the planner chooses the probability with which a meeting between a worker employed in a match with productivity z in location l and a firm in any possible destination location $k \in K$ is turned into a match given the signal s, $h_e(s,z,l,k)$: $Z \times Z \times K \times K \to [0,1]$; given this set of choices, the planner chooses the probability that a worker employed in a match of productivity z in location l will match with a firm conditional on s: $h_e^{max}(s,z,l)$: $Z \times K \times K \to [0,1]$.

Given the choices of the social planner, $\Omega = \{d_e,\ d_u,\ \eta_m^{max},\ \eta_u^{max},\ \eta_e^{max},\ \theta_u^{max},\ \theta_e^{max},\ h_u^{max},\ h_e^{max}\}$, aggregate consumption is given by total production minus relocation costs and search costs:

$$
\begin{aligned}
F(\Omega|\psi) = & \sum_{k\in K}\{b_k\,\widehat{u}_k\} + \sum_{k\in K}\sum_{z\in Z}\{(\pi(y,\mu_k)+z)\,\widehat{g}(z,k)\} \\
& + \sum_{k\in K}\left\{A_k^u \times \widehat{u}_k + A_k^e \times \sum_{z\in Z}\widehat{g}(z,k)\right\} \\
& - \sum_{k\in K}\left\{\eta_m^{max}(k)\left(\frac{\tau}{N(k)} + d_u(k)u_k + \sum_{z\in Z}[d_e(z,k)g(z,k)]\right) \times c_u(k,k^*)\right\} \\
& - (1-\tau)\lambda_u \sum_{k\in K}\left\{\eta_u^{max}(k)(1-d_u(k))p(\theta_u^{max}(k)) \times \right. \\
& \qquad \left. \times\, \mathbb{E}_s[\alpha_{kk^*}h_u^{max}(s,k) + (1-\alpha_{kk^*})m_u^{max}(k)](u_k - \widehat{ns}_k)c_u(k,k^*)\right\} \\
& - (1-\tau)\lambda_e \sum_{k\in K}\sum_{z\in Z}\left\{\eta_e^{max}(z,k)\,[1-d_e(z,k)]\,p(\theta_e^{max}(z,k)) \times \right. \\
& \qquad \left. \times\, \mathbb{E}_s[\alpha_{kk^*}h_e^{max}(s,z,k) + (1-\alpha_{kk^*})m_e^{max}(z,k)]g(z,k)c_e(k,k^*)\right\} \\
& - (1-\tau)\xi\lambda_u \sum_{k\in K}\{[(1-d_u(k))\theta_u^{max}(k)]\,(u_k - \widehat{ns}_k)\} \\
& - (1-\tau)\xi\lambda_e \sum_{k\in K}\sum_{z\in Z}\{[1-d_e(z,k)]\ \theta_e^{max}(z,k)g(z,k)\},
\end{aligned}
\tag{A1}
$$

where k^* denotes the destination location for any source location k, and $\widehat{u}_k$, $\widehat{g}(z,k)$ denote the distribution of individuals across employment states, locations, and sub-markets at the production stage and at the beginning of the next period.

A.1 The Social Planner's Value Function

The social planner maximises the sum of current and future aggregate consumption discounted at the factor β. Hence, the planner's value function, $W(\psi)$, solves the following Bellman equation:

$$W(\psi) = \max_{\Omega}\{F(\Omega|\psi) + \beta\mathbb{E}W(\widehat{\psi})\} \tag{A2}$$

subject to (1), (2), (3), and

$$\begin{array}{lll} d_e : Z \times K \to [\delta, 1], & d_u(l) : K \to [0,1], & \eta_m^{max}(l) : K \to [0,1], \\ \eta_u^{max}(l) : K \to [0,1], & \eta_e^{max}(z,l) : Z \times K \to [0,1], & \theta_u^{max}(l) : K \to \mathbb{R}_+, \\ \theta_e^{max}(z,l) : Z \times K \to \mathbb{R}_+, & h_u^{max}(s,l) : Z \times K \to [0,1], & h_e^{max}(s,z,l) : Z \times K \times K \to [0,1] \end{array}$$

A.1.1 Separability of the Social Planner's Problem

The social planner's value function, $W(\psi)$, depends on the aggregate productivity, y, the measure of workers who are unemployed across $N(k)$ locations, u, and the measure of workers who are employed in $N(z)$ submarkets across $N(k)$ locations, g. Directed search (and the self-selection it implies) enables this decomposition of the Planner's problem into worker-specific problems.

Consider the planner's value function $W(\psi)$, which solves (A2); it is possible to express $W(\psi)$ as follows:

$$\begin{aligned} W(\psi) = \sum_k \{Q_u^{max}(k,y) \times ns_k\} + \sum_k \{W_u(k,y) \times (u_k - ns_k)\} \\ + \sum_k \sum_z \{W_e(z,k,y) g(z,k)\}, \end{aligned} \tag{A3}$$

where $Q_u^{max}(k,y)$, $W_u(k,y)$, $W_e(z,k,y)$ are the component value functions for the unemployed non-searchers in location k, the unemployed job-seekers in location k, and the workers employed in matches of productivity z in location k, respectively.

A.1.2 Component Value Functions

Inspection of (A3) suggests that the social planner's value function, $W(\psi)$, is linear in u and g. This implies that the social planner's problem is equivalent to solving $(N(z) + 2) \times N(k)$ smaller problems, each one of which is associated with workers in a particular submarket, and/or employment state, and/or location. The planner's problem is equivalent to the optimisation of the following component value functions subject to the constraints given in equation (A2).

The component value function for the unemployed is:[9]

$$W_u(l,y) = \max_{d_u}\{d_u \times Q_u^{max}(l,y) + (1 - d_u) \times S_u^{max}(l,y)\} \tag{A4}$$

where $S_u^{max}(l,y)$ is the component value function for the unemployed job-seekers in location l and $Q_u^{max}(l,y)$ is the component value function for the unemployed non-searchers. $S_u^{max}(l,y)$ solves

$$S_u^{max}(l,y) = \max\{S_u(l,1,y), S_u(l,2,y), \ldots, S_u(l,K),y)\}, \tag{A5}$$

[9] To keep the notation manageable, $\{\theta_u, h_u, m_u\}$ is used to denote both $\{\theta_u(l,k), h_u(l,k), m_u(l,k)\}$ and $\{\theta_u(l,l), h_u(l,l), m_u(l,l)\}$.

where $S_u(l,k,y)$ is the value of an unemployed job-seeker in l searching for a match in $k \in K$

$$\begin{aligned}S_u(l,k,y) = \max_{\eta_u,\theta_u,h_u} \{ & -(1-\eta_u)\,\xi\lambda_u\theta_u - \eta_u\,\xi\lambda_u\theta_u \\ & + [1-\eta_u]([1-\lambda_u p(\theta_u)m_u][b_l + A_l^u + \beta\mathbb{E}W_u(l,\widehat{y})] \\ & + \lambda_u p(\theta_u)\mathbb{E}_s[\alpha_{ll}h_u(s) + (1-\alpha_{ll})m_u][\pi(y,\mu_l) + s + A_l^e + \beta\mathbb{E}W_e(s,l,\widehat{y})]) \\ & + \eta_u([1-\lambda_u p(\theta_u)m_u][b_l + A_l^u + \beta\mathbb{E}W_u(l,\widehat{y})] \\ & + \lambda_u p(\theta_u)\mathbb{E}_s[\alpha_{lk}h_u(s) + (1-\alpha_{lk})m_u][\pi(y,\mu_k) + s + A_k^e - c_u(l,k) + \beta\mathbb{E}W_e(s,k,\widehat{y})]) \\ & \} \end{aligned} \tag{A6}$$

Similarly, $Q_u^{max}(l,y)$ solves

$$Q_u^{max}(l,y) = \max\{Q_u(l,1,y), Q_u(l,2,y), \ldots, Q_u(l,K,y)\}, \tag{A7}$$

where $Q_u(l,k,y)$ is the value of an unemployed non-searcher in l who examines the possibility of relocating to $k \in K$

$$\begin{aligned}Q_u(l,k,y) = \max_{\eta_m}\{ & (1-\eta_m)(b_l + A_l^u + \beta\mathbb{E}W_u(l,\widehat{y})) \\ & + \eta_m(b_k + A_k^u - c_u(l,k) + \beta\mathbb{E}W_u(k,\widehat{y}))\}\end{aligned} \tag{A8}$$

The component value function for the employed is:[10]

$$W_e(z,l,y) = \max_{d_e}\{d_e \times Q_u^{max}(l,y) + (1-d_e) \times S_e^{max}(z,l,y)\}, \tag{A9}$$

where $S_e^{max}(z,l,y)$ is the component value function for workers employed in matches of productivity z in location l and $Q_u^{max}(l,y)$ is the component value function for the unemployed non-searchers, given by (A7). $S_e^{max}(z,l,y)$ solves

$$S_e^{max}(z,l,y) = \max\{S_e(z,l,1,y), S_e(z,l,2,y), \ldots, S_e(z,l,K,y)\}, \tag{A10}$$

where $S_e(z,l,k,y)$ is the value of a worker employed in a match of productivity z in l searching for a match in $k \in K$

$$\begin{aligned}S_e(z,l,k,y) = \max_{\eta_e,\theta_e,h_e} \{ & \\ & -[1-\eta_e(z)][1-d_e]\xi\lambda_e\theta_e - \eta_e(z)[1-d_e]\xi\lambda_e\theta_e \\ & + [1-\eta_e(z)][1-d_e][1-\lambda_e p(\theta_e)m_e][\pi(y,\mu_l) + z + A_l^e + \beta\mathbb{E}W_e(z,l,\widehat{y})] \\ & + [1-\eta_e(z)][1-d_e]\lambda_e p(\theta_e)\mathbb{E}_s[\alpha_{ll}h_e(s) + (1-\alpha_{ll})m_e][\pi(y,\mu_l) + s + A_l^e + \beta\mathbb{E}W_e(s,l,\widehat{y})] \\ & + \eta_e(z)[1-d_e][1-\lambda_e p(\theta_e)m_e][\pi(y,\mu_l) + z + A_l^e + \beta\mathbb{E}W_e(z,l,\widehat{y})] \\ & + \eta_e(z)[1-d_e]\lambda_e p(\theta_e)\mathbb{E}_s[\alpha_{lk}h_e(s) + (1-\alpha_{lk})m_e][\pi(y,\mu_k) + s + A_k^e - c_e(l,k) + \beta\mathbb{E}W_e(s,k,\widehat{y})] \\ & \}\end{aligned} \tag{A11}$$

[10]As in the previous footnote, $\{\theta_e, h_e, m_e\}$ is used to denote both $\{\theta_e(z,l,k,y), h_e(z,l,k,y), m_e(z,l,k,y)\}$ and $\{\theta_e(z,l,l,y), h_e(z,l,l,y), m_e(z,l,l,y)\}$.

A.2 Who Moves, When and Where? The Solution to the Social Planner's Problem

The planner's problem can be decomposed into worker-specific problems that depend only on the aggregate productivity because the search process is directed. In this section, we provide a description of the solution. The planner solves the following $(N(z)+2) \times N(k)$ problems, each one of which corresponds to individuals in a particular location, employment state, and submarket.

A.2.1 Unemployed Non-Searchers

There are $N(k)$ problems for unemployed non-searchers. The planner solves each one of these problems in two steps. First, conditional on the non-searchers' current location, l, the planner makes pairwise comparisons of non-searchers' lifetime utility in l and their corresponding utility in every possible destination location k (accounting for moving costs), and chooses $\eta_m^*(l,k,y)$, which determines whether an unemployed non-searcher is better-off staying in her current location or moving to location k. In particular, the efficient choice of $\eta_m(l,k,y)$ is $\eta_m^*(l,k,y)=1$ if

$$b_l + A_l^u + \beta \mathbb{E} W_u(l,\widehat{y}) \leq b_k + A_k^u + \beta \mathbb{E} W_u(k,\widehat{y}) - c_u(l,k) \tag{A12}$$

and $\eta_m^*(l,k,y)=0$ otherwise.

Having made all possible pairwise comparisons between the current location and destination locations, the planner then chooses $\eta_m^{max}(l,y)=\eta_m^*(l,k^*,y)$ where $k^* \in K$ is the destination location that maximises the present value of the lifetime utility of unemployed non-searchers, as given by equation (A7).

A.2.2 Unemployed Job-Seekers

There are $N(k)$ problems for unemployed job-seekers. The planner solves each one of these problems in three steps. First, conditional on the unemployed job-seekers' current location, l, the planner chooses $d_u^*(l,y)$, which determines whether job-seekers are better-off stopping their search and becoming non-searchers or continuing their search for matches. Specifically, the efficient choice of $d_u(l,y)$ is $d_u^*(l,y)=1$ if

$$Q_u^{max}(l,y) \geq S_u^{max}(l,y) \tag{A13}$$

and $d_u^*(z,l,y)=\delta$ otherwise (see (A4)).

In the second step the planner makes pairwise comparisons of job seekers' lifetime utility in l and their corresponding utility in every possible destination location k (accounting for search and moving costs), and chooses $\eta_u^*(l,k,y)$, $\theta_u^*(l,k,y)$, and $h_u^*(s,l,k,y)$, which determine whether an unemployed job-seeker is better-off searching for a match in her current location or in location k. In particular, the efficient choice of $\eta_u(l,k,y)$ is $\eta_u^*(l,k,y)=1$ if

$$\begin{aligned}
&-\xi\lambda_u\theta_u^*(l,l,y)+[1-\lambda_u p(\theta_u^*(l,l,y))m_u^*][b_l+A_l^u+\beta\mathbb{E}W_u(l,\widehat{y})]\\
&+\lambda_u p(\theta_u^*(l,l,y))\mathbb{E}_s[\alpha_{ll}h_u^*(s)+(1-\alpha_{ll})m_u^*][\pi(y,\mu_l)+s+A_l^e\\
&+\beta\mathbb{E}W_e(s,l,\widehat{y})]\leq\\
&-\xi\lambda_u\theta_u^*(l,k,y)+[1-\lambda_u p(\theta_u^*(l,k,y))m_u^*][b_l+A_l^u+\beta\mathbb{E}W_u(l,\widehat{y})]\\
&+\lambda_u p(\theta_u^*(l,k,y))\mathbb{E}_s[\alpha_{lk}h_u^*(s)+(1-\alpha_{lk})m_u^*][\pi(y,\mu_k)+s+A_k^e-c_u(l,k)\\
&+\beta\mathbb{E}W_e(s,k,\widehat{y})]
\end{aligned}\tag{A14}$$

and $\eta_u^*(l,k,y)=0$ otherwise (see (A6)).
The efficient choice of $\theta_u(l,k,y)$ solves:

$$\begin{aligned}
\xi\geq p'(\theta_u^*(l,k,y))\sum_{s\geq r_u^*(l,k)}&(\alpha_{lk}\{\pi(y,\mu_k)+s+A_k^e-b_l-A_l^u-c_u(l,k)\\
&+\beta\mathbb{E}[W_e(s,k,\widehat{y})-W_u(l,\widehat{y})]\}+\\
&+(1-\alpha_{lk})\mathbb{E}_{z'}\{\pi(y,\mu_k)+z'+A_k^e-b_l-A_l^u-c_u(l,k)\\
&+\beta\mathbb{E}[W_e(z',k,\widehat{y})-W_u(l,\widehat{y})]\})f(s)
\end{aligned}\tag{A15}$$

Finally, the efficient choice of $h_u(s,l,k,y)$ is $h_u^*(s,l,k,y)=1$ if

$$\begin{aligned}
b_l+A_l^u+\beta\mathbb{E}W_u(l,\widehat{y})]+c_u(l,k)\leq\alpha_{lk}[\pi(y,\mu_k)+s+A_k^e+\beta\mathbb{E}W_e(s,k,\widehat{y})]+\\
+(1-\alpha_{lk})\mathbb{E}_{z'}[\pi(y,\mu_k)+z'+A_k^e+\beta\mathbb{E}W_e(z',k,\widehat{y})]
\end{aligned}\tag{A16}$$

and $h_u^*(s,l,k,y)=0$ otherwise

Having made all possible pairwise comparisons between the current location and destination locations, the planner then chooses in step 3 $\eta_u^{max}(l,y)=\eta_u^*(l,k^*,y)$, $\theta_u^{max}(l,y)=\theta_u^*(l,k^*,y)$, and $h_u^{max}(s,l,y)=h_u^*(s,l,k^*,y)$ where $k^*\in K$ is the destination location that maximises the present value of the lifetime utility of unemployed job-seekers (as given by equation (A5)).

A.2.3 Employed Workers

There are $N(z)\times N(k)$ problems for employed workers. The planner solves each one of these problems in three steps. First, conditional on the idiosyncratic productivity of the workers' current match, z, and conditional on the workers' current location, l, the planner chooses $d_e^*(z,l,y)$, which determines whether workers are better-off separating or remaining employed in this type of match. Specifically, the efficient choice of $d_e(z,l,y)$ is $d_e^*(z,l,y)=1$ if

$$Q_u^{max}(l,y)\geq S_e^{max}(z,l,y)\tag{A17}$$

and $d_e^*(z,l,y)=\delta$ otherwise. (See (A9))

In the second step the planner makes pairwise comparisons of workers' lifetime utility in l and their corresponding utility in every possible destination location k (accounting for search and moving costs), and chooses $\eta_e^*(z,l,k,y)$, $\theta_e^*(z,l,k,y)$, and $h_e^*(s,z,l,k,y)$, which determine whether a worker employed in a match of productivity z is better-off searching for a match in her current location, l, or in location k.

In particular, the efficient choice of $\eta_e(z,l,k,y)$ is $\eta_e^*(z,l,k,y)=1$ if

$$\begin{aligned}
&-\xi\lambda_e\theta_e^*(z,l,l,y)+[1-\lambda_e p(\theta_e^*(z,l,l,y))m_e^*][\pi(y,\mu_l)+z+A_l^e+\beta\mathbb{E}W_e(z,l,\widehat{y})]\\
&+\lambda_e p(\theta_e^*(z,l,l,y))\mathbb{E}_s[\alpha_{ll}h_e^*(s)+(1-\alpha_{ll})m_e^*][\pi(y,\mu_l)+s+A_l^e\\
&+\beta\mathbb{E}W_e(s,l,\widehat{y})]\leq\\
&-\xi\lambda_e\theta_e^*(z,l,k,y)+[1-\lambda_e p(\theta_e^*(z,l,k,y))m_e^*][\pi(y,\mu_l)+z+A_l^e+\beta\mathbb{E}W_e(z,l,\widehat{y})]\\
&+\lambda_e p(\theta_e^*(z,l,k,y))\mathbb{E}_s[\alpha_{lk}h_e^*(s)+(1-\alpha_{lk})m_e^*][\pi(y,\mu_k)+s+A_k^e-c_e(l,k)\\
&+\beta\mathbb{E}W_e(s,k,\widehat{y})]
\end{aligned}\tag{A18}$$

and $\eta_e^*(z,l,k,y)=0$ otherwise (see (A11)).

The efficient choice of $\theta_e(z,l,k,y)$ solves:

$$\begin{aligned}
\xi\geq p'(\theta_e^*(z,l,k,y))\times\sum_{s\geq r_e^*(z,l,k,y)}&(\alpha_{lk}\{\pi(y,\mu_k)-\pi(y,\mu_l)+s-z+A_k^e-A_l^e-c_e(l,k)\\
&\quad+\beta\mathbb{E}[W_e(s,k,\widehat{y})-W_e(z,l,\widehat{y})]\}\\
&+(1-\alpha_{lk})\mathbb{E}_{z'}\{\pi(y,\mu_k)-\pi(y,\mu_l)+z'-z+A_k^e-A_l^e-c_e(l,k)\\
&\quad+\beta\mathbb{E}[W_e(z',k,\widehat{y})-W_e(z,l,\widehat{y})]\})f(s)
\end{aligned}\tag{A19}$$

Finally, the efficient choice of $h_e(s,z,l,k,y)$ is $h_e^*(s,z,l,k,y)=1$ if

$$\begin{aligned}
\pi(y,\mu_l)+z+A_l^e+\beta\mathbb{E}W_e(z,l,\widehat{y})+c_e(l,k)\leq{}&\alpha_{lk}[\pi(y,\mu_k)+s+A_k^e+\beta\mathbb{E}W_e(s,k,\widehat{y})]\\
&+(1-\alpha_{lk})\mathbb{E}_{z'}[\pi(y,\mu_k)+z'+A_k+\beta\mathbb{E}W_e(z',k,\widehat{y})]
\end{aligned}\tag{A20}$$

and $h_e^*(s,z,l,k,y)=0$ otherwise.

Having made all possible pairwise comparisons between the current location and destination locations, the planner then chooses in step 3 $\eta_e^{max}(z,l,y)=\eta_e^*(z,l,k^*,y)$, $\theta_e^{max}(z,l,y)=\theta_e^*(z,l,k^*,y)$, and $h_e^{max}(s,z,l,y)=h_e^*(s,z,l,k^*,y)$ where $k^*\in K$ is the destination location that maximises the present value of the lifetime utility of employed job-seekers (as given by equation (A10)).

B Computational Details and Validation Studies

B.1 Moments used in the GMM criterion

The GMM objective function, see (13), calculates the distance between data moments and model generated moments. Table B1 presents the data and model simulated moments considered in our estimation. Labour market transitions are considered by segment and local labour market, while regional transitions and unemployment are aggregated across segments at the local labour market level.[11]

Table B1: GMM moments

data moments	model-based moments	
local $e^{sec} \rightarrow e^{sec}$ transition rate	ee_l^{sec}	see eq. (B1)
local $e^{sec} \rightarrow u$ transition rate	eu_l^{sec}	see eq. (B2)
local sectoral employment share	g_l^{sec}	see eq. (B3)
local unemployment	$unemp_l$	see eq. (B4)
relocations into l	$reloc_l$	see eq. (B5)

Notes. Data moments based on LIAB 2002-2008, time-averaged. Subscript l denotes (destination) travel to work area, superscript sec denotes sector.

To calculate the job-to-job transition rate, we examine flows into matches of productivity z in segment sec at TTWA l between the beginning of the period and the production stage. The job-to-job transition rate is then determined by dividing the total number of flows into $z \forall z \in Z$ by total employment in segment sec at TTWA l at the beginning of the period, see (B1): for each segment, we first compute the number of workers who, at the beginning of the period, were employed in a match of productivity z' in location l and moved into a match of productivity z in TTWA l, and the number of workers who, at the beginning of the period, were employed in a match of productivity z' in location k' and moved into a match of productivity z in TTWA l; we then aggregate across productivity levels ($\forall z \in Z$) and divide by the local sectoral employment level at the beginning of the period.

$$\begin{aligned} ee_l^{sec} = & \frac{1}{\sum\limits_{z \in Z} g(z,l)} \times (1-\tau) \times \sum_{z \in Z} \Bigg\{ \sum_{z' \in Z} \Bigg\{ g(z',l)[1-d_e^*(z',l)] \times \\ & \qquad \times [1-\eta_e^{max}(z',l)] \lambda_e p(\theta_e^{max}(z',l)) h_e^{max}(z,z',l) f(z) \Bigg\} + \\ & + \sum_{k' \in K} \Bigg\{ \sum_{z' \in Z} \Bigg\{ g(z',k')[1-d_e^*(z',k')] \eta_e^{max}(z',k',l) \times \\ & \qquad \times \lambda_e p(\theta_e^{max}(z',k',l)) h_e^{max}(z,z',k') f(z) \Bigg\} \Bigg\} \quad \Bigg\} \end{aligned} \tag{B1}$$

[11] To keep the notation manageable, we suppress the sectoral superscript from the right-hand-sides of equations (B1)-(B6).

Similarly, to calculate the job-to-unemployment transition rate, we compute all the job separations in segment sec at TTWA l that occurred between the beginning of the period and the production stage, and divide by the local sectoral employment level at the beginning of the period.

$$eu_l^{sec} = \frac{1}{\sum_{z \in Z} g(z,l)} \times \left\{ \tau \times \sum_{z \in Z} g(z',l) + (1-\tau) \times \sum_{z \in Z} \left\{ d_e^*(z,l) g(z,l) \right\} \right\} \quad \text{(B2)}$$

Local employment in every sector is expressed as a share of the total employment in this sector across all local labour markets

$$g_l^{sec} = \frac{\sum_{z \in Z} g(z,l)}{\sum_{k \in K} \sum_{z \in Z} g(z,k)} \quad \text{(B3)}$$

The remaining moments used in our GMM objective function are aggregated across segments at the TTWA level. We consider local unemployment levels at TTWA l and relocation flows into l at the production stage of the period. Local unemployment is given by

$$unemp_l = \sum_{sec} u_l^{sec} \quad \text{(B4)}$$

where sec denotes segment, and u_l^{sec} is given by (2).[12]

Similarly, relocation flows into l are given by

$$reloc_l = \sum_{sec} reloc_l^{sec} \quad \text{(B5)}$$

where $reloc_l^{sec}$ denotes relocation flows into l for segment sec. To calculate segment specific relocation flows into l, we first compute the number of regional flows into matches of productivity z in TTWA l aggregated across origin labour market state (unemployment or employment in a match of productivity z'), and also aggregated across origin TTWA ($\forall k' \in K_{-l}$); we then aggregate across productivity levels ($\forall z \in Z$), and add regional flows into the unemployment pool of TTWA l, which include

[12]Note that in the presentation of our model, we only consider one segment, so (2) presents u_l as total unemployment in travel to work area l.

unemployed non-searchers or new entrants.

$$
\begin{aligned}
reloc_l^{sec} =&(1-\tau) \times \sum_{z \in Z} \Bigg\{ \sum_{k' \in K} \Bigg\{ u_{k'}[1-d_u(k')]\eta_m^{max}(k')\lambda_u p(\theta_u^{max}(k')) \times h_u^{max}(z,k')f(z) + \\
&\qquad\qquad + \sum_{z' \in Z} \Bigg\{ g(z',k')[1-d_e^*(z',k')]\eta_e^{max}(z',k',l) \times \\
&\qquad\qquad\qquad \lambda_e p(\theta_e^{max}(z',k',l))h_e^{max}(z,z',k')f(z) \Bigg\} \quad \Bigg\}\Bigg\} + \\
&+ (1-\tau) \times \Bigg\{ \sum_{k' \in K} \eta_m^{max}(k',l) \times \Bigg(d_u(k') \times u_{k'} + \sum_{z \in Z} [d_e(z,k')g(z,k')] \Bigg) \Bigg\} + \\
&+ \frac{\tau}{N(k)} \times \Bigg\{ [1-\eta_m^{max}(l)] + \sum_{k' \in K} \eta_m^{max}(k',l) \Bigg\}
\end{aligned} \tag{B6}
$$

B.2 Computational Details: An Evolutionary Algorithm

In the empirical implementation of the model, we segment the economy by industry in order to accommodate better worker and firm heterogeneity. Specifically, we consider explicitly the manufacturing sector and services, and denote sector *sec* by the superscript (sec). Then the sector-specific parameters are the frictional parameters ($\lambda_e^{(sec)}$ and $\delta^{(sec)}$), and the vacancy posting cost ($\xi^{(sec)}$). We also allow the sector to affect the moving cost, captured by a parameter $\alpha_1^{(sec)}$, since the industrial composition of the location might affect its attractiveness to workers. Since we take location and sector specific firm productivity as given (measured by the external estimates of the average firm fixed effect in the location and the sector), the location specific parameters only enter the moving cost function. Since the attractiveness of a location (e.g. amenities) is unlikely to be captured by the house price alone, we include destination fixed effects.

Our estimation algorithm reflects that the moving cost function is, apart from the coefficient $\alpha_1^{(sec)}$, sector invariant. This is achieved by switching successively between estimating global sector specific parameters given the location specific parameters, and estimating location specific parameters given global sector specific ones. Each such inner and outer loop features a minimisation of the GMM criterion, see (13), which is a function of the distance between the empirical and simulated model-based moments. We use the moments presented in Table (B1).

In principle, the minimisation problem could be solved by an application of the Nelder Mead algorithm. In practice, this is very slow given the high dimensionality of our set-up, and we use Nelder Mead only for local refinements once a "good" estimate is obtained from our evolutionary estimation approach. Its comparative strength it its speed since it is paralleliseable. The evolutionary optimisation algorithm is as follows:

step (i) generate a "population", equal to N, of randomly drawn parameter vectors within the lower and upper bounds for the parameters to be estimated;

step (ii) evaluate the objective function N times and sort parameter vectors by the corresponding "fitness" (i.e. objective function) value;

step (iii) pick the S (where $S < N$) best fitness parameter vectors and store them, discard the remaining parameter vectors;

step (iv) generate R (where $R < N$) randomly drawn parameter vectors as in step (i); generate M (where $M+R \leq N$) new parameter vectors that correspond to linear combinations of the stored S parameter vectors; generate B (where $B+M+R \leq N$) new parameter vectors, such that $B = (1+p) \times S$, where $p \in [-0.1, 0.1]$; use the minimum and maximum values of each parameter in the stored S parameter vectors as the new lower and upper bounds and generate $N - R - B - M$ randomly drawn parameter vectors within these new (contracted) lower and upper bounds;

step (v) using the new population of $R+M+B+S = N$ parameter vectors repeat steps (ii)-(iv)

step (vi) repeat until I different populations of N parameter vectors have been generated and evaluated.

B.3 Validation Experiments

B.3.1 A Simple Cost Function

The first validation experiment considers a simplified setting for only one sector and a moving cost function given by

$$c(l,k) = \alpha_0 + \alpha_1 \times \Delta hp(l,k) + \alpha_2 \times distance(l,k) \tag{B7}$$

The objective is to estimate λ_e, δ, ξ as well as $\alpha = (\alpha_0, \alpha_1, \alpha_2)$. All other parameters are set as described in Section 5.3. We consider models with 3 and 30 locations (which correspond to the largest TTWAs in our German data). This is also the setting we have considered in the numerical identification illustration of Section 5.2.1. In view of the modest number of parameters to estimate, we use the Nelder Meade algorithm in the optimisation.

Tables B2 and B3 reports the results. The population parameters have been chosen so that aggregate transitions are of similar magnitudes as encountered in our data. For instance, in the model with 30 locations, the true unemployment rate is close to 5%, and the rate of relocations about 1.4%. Turning to the parameter estimates, it is evident that the estimation algorithm works very well, as we get very close to the population parameter values. The fit of the estimated model is thus close to perfect.

Table B2: Validation experiment I (simple cost function): 3 locations

	pop. value	estimates	Model Fit	true	model
λ_e	.85	.849985	unemployment [%]	.0494	.0494
δ	.026	.0260015	relocations [%]	.010	.010
ξ	3.65	3.64865	e $\rightarrow$ u transitions [%]		
α_0	1.0	2.53078	u $\rightarrow$ e transitions [%]	.03896	.0390
α_1	.004	3.05276e-6	e $\rightarrow$ e transitions [%]	.0542	.0542
α_2	5.0	3.89439			

Notes: Moving cost function given by equation (B7). Optimisation using the Nelder-Mead algorithm. Value of objective function at estimates: 1.045e-06.

Table B3: Validation experiment I (simple cost function): 30 locations

	pop. value	estimates	Model Fit	true	model
λ_e	.85	.850026	unemployment [%]	.04798	.04798
δ	.026	.0259993	relocations [%]	.01447	.01447
ξ	3.65	3.65068	e $\rightarrow$ u transitions [%]		
α_0	1.0	0.985743	u $\rightarrow$ e transitions [%]	.03899	.03899
α_1	.004	.00410253	e $\rightarrow$ e transitions [%]	.054263	.054263
α_2	5.0	5.29953			

Notes: As per Table B3. Value of objective function at estimates: 5.376140e-07

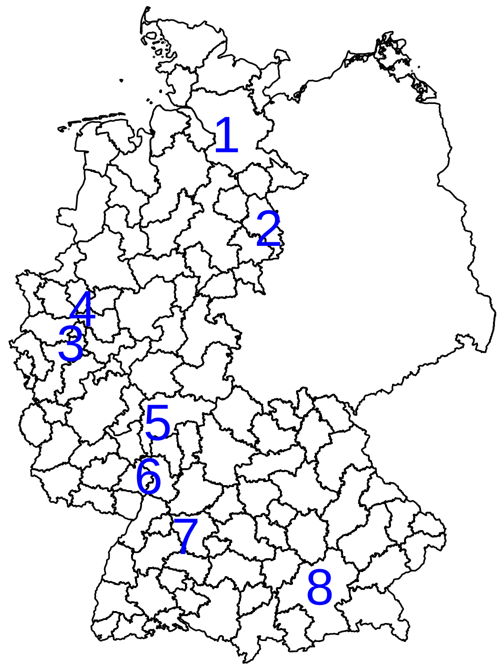
C Data Appendix

C.1 8 selected local labour markets

In order to illustrate further and in more specific detail the spatial heterogeneity of local labour markets, and the observed patterns of geographic mobility, we report summary statistics for 8 selected local labour markets. These include the largest and economically most important cities (Hamburg, Frankfurt, Munich) and a selection of smaller ones (such as Bochum or Wolfsburg). These 8 local labour markets are depicted on the map of Figure C1.

Table C1 reports some summary statistics. It is evident that these local labour markets differ markedly in terms of unemployment rates, wages, living costs, as well as productivities. For instance, the mean unemployment rate in the TTWA of Bochum is 2.4 times higher than that of Munich, while the mean daily wage in the former is 91% of the latter. The largest mean daily wage is paid in the TTWA of Frankfurt, which also exhibits the largest mean worker fixed effect and the largest firm fixed effect in services, the latter being expected given the area's central role in banking and finance. Wolfsburg is a comparatively small TTWA and, as the seat of car manufacturer Volkswagen, being the principal employer, exhibits the largest firm fixed effect in manufacturing; since its workforce is mainly employed in blue collar

Figure C1: Eight selected travel-to-work areas.



Notes: 8 Local labour markets (TTWAs): 1: Hamburg, 2: Wolfsburg, 3: Leverkusen, 4: Bochum, 5: Frankfurt, 6: Mannheim, 7: Stuttgart, 8: München.

occupations, it is no contradiction that the mean daily wage and the mean worker fixed effect are fairly low, as are housing costs. Stuttgart, by comparison, is much larger and much more diversified industrially, which is manifested in a smaller mean firm fixed effect in manufacturing but a larger worker fixed effect. Overall, the TTWA of Munich is the most expensive to inhabit.

Table C2 describes the geographic mobility among these 8 selected local labour markets (and all others aggregated in the cells labelled 'Rest'). The table reveals that, conditional on being located in a big urban zone (such as Hamburg, Frankfurt, or Munich), the worker is more likely to relocate to another such urban zone than to a smaller urban zone. For instance, originating in the TTWA of Munich, moves to Wolfsburg, Bochum or Mannheim are extremely unlikely. However, spatial moves are not exhausted by the 8 selected TTWA, as the residual category exceeds by at least one order of magnitude all other conditional probabilities.

Table C1: Eight local labour markets

no.	TTWA name	# of districts	inhabitants $[\times 10^6]$	mean u rate	rel. house price index	rel. mean daily wage	rel. mean worker FE	rel. mean firm FE (man)	rel. mean firm FE (serv)
1	Hamburg	8	3.19	10.02	0.75	0.94	0.987	0.954	0.895
2	Wolfsburg	3	0.39	10.37	0.58	0.85	0.979	1.051	0.811
3	Leverkusen	5	2.04	11.49	0.74	1.04	0.983	1.021	0.946
4	Bochum	4	1.05	14.90	0.60	0.91	0.975	1.026	0.866
5	Frankfurt	8	2.49	8.55	0.80	1.05	1.022	1.008	1.031
6	Mannheim	8	0.98	9.53	0.67	0.82	0.963	1.048	0.836
7	Stuttgart	4	1.99	6.12	0.82	0.94	0.983	1.016	0.962
8	Munchen	11	2.65	6.20	1	1	1	1	1

Notes: See Table 1. Columns 4 and 5: District-level data obtained from www.regionalstatistik.de: Col. 4 (inhabitants) Table 173-01-4 for year 2002, Col. 5 (mean unemployment rate) Table 659-71-4 averaged over 2002-2008. Columns 9 and 10: ‘man’ refers to manufacturing, ‘serv’ to services.

Table C2: Spatial mobility across TTWAs

	1 [H]	2 [Wo]	3 [Lev]	4 [Bo]	5 [Fr]	6 [Man]	7 [Stut]	8 [Mun]	Rest
1 [H]		0.037	0.286	0.106	0.550	0.057	0.203	0.475	10.363
2 [Wo]	0.052		0.018	0.016	0.024	0.001	0.011	0.011	1.194
3 [Lev]	0.243	0.019		0.143	0.240	0.050	0.104	0.174	5.603
4 [Bo]	0.098	0.004	0.132		0.082	0.014	0.048	0.073	3.780
5 [Fr]	0.415	0.018	0.250	0.114		0.169	0.224	0.342	6.401
6 [Man]	0.048	0.006	0.042	0.016	0.200		0.097	0.057	2.603
7 [St]	0.220	0.010	0.101	0.050	0.190	0.092		0.196	5.715
8 [Mun]	0.466	0.013	0.229	0.090	0.437	0.070	0.267		6.455
Rest	12.252	1.070	7.481	3.714	8.419	2.918	6.422	7.911	

Notes: Bi-stochastic transition matrix for moves between selected TTWAs. The category labelled "Rest" aggregates all other TTWA. Based on LIAB, time period 2002-2008. Reported is $s_{l,k}$ = number of relocations from l to k divided by the total number of relocations in Germany. By definition $\sum_l \sum_k s_{l,k} = 100$.