# Job Map and Cartographic Analyses of Occupational Labour Markets

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Job Map and Cartographic Analyses of Occupational Labour Markets

Yuzuru ISODA*

Abstract  Research on occupational labour markets and occupational mobility is plagued by the problem of defining occupations. To overcome this problem, this article projects occupation categories onto a two-dimensional space to create a “job map”, based on multidimensional scaling applied to occupational change data. A job map provides intuitive information to individuals intending to change jobs or planning a career path. Once a job map is created, various methods used in geographical information science and spatial statistical analyses can be applied. Examples include visualizing the flows of occupational changes and estimating wages, unemployment, and other indicators using spatial interpolation techniques. Job map can yield a systematic understanding of relationships among occupation categories and potentially standardise jobs in different classification schemes over time and across space.

Key words: occupational mobility, occupational classification, visualization, gravity model, geographical information system, multidimensional scaling

1. Introduction

The literature on occupational mobility is very limited compared with the voluminous literature on geographical mobility. Yet occupational mobility is an important area of research, of social concern. Occupational change facilitates better matches between of jobs and people, resulting in higher productivity (Eriksson 1991; Light and McGarry 1998). Engaging in different jobs is also a learning process that result in acquisition of sets of skills, a means of accumulating human capital (Rosen 1972; Sicherman and Galor 1990); providing an opportunity for individual income growth even when national income is at stagnation (Shaw 1987). To be sure, occupational change is not without its costs. Rapid structural changes in an economy mandating occupational change demand individuals or the society to bear the costs of transition (Parrado et al. 2007). This cost can be mitigated if occupation-specific human capital can be transferred to a new job after a job change (Shaw 1978; Kambourova and Manovskii 2008). After all, occupational mobility is the main ingredient of social mobility, which is a prerequisite for social equality.

This article addresses that the main obstacle to research on occupational mobility is the identification of occupations, which are difficult to quantitatively define and measure (Shaw 1987). Standardization of occupational classification has been established in most developed
nations, but the structure or relationships between large numbers of categorized occupations are not identified or known. This article attempts to establish a method of understanding the relationships between occupation categories that can be used for further research on occupational labour markets and mobility.

What is not known to researchers is not known to individual workers. Very little systematic information is provided to those considering a job change on what alternative jobs are available to them, which occupations utilize their previous experiences, what the current labour market state of a particular occupation is, and how they should plan a future career path. The initial motivation of this article was to provide such information in an intuitive way, through the use of a map.

Map of jobs can be produced by placing occupations on an abstract space, preferably on a two-dimensional space, in such a way that relationships among occupations conforms to the 'first law of geography' (Tobler 1970; Sui 2004); near occupations are more related than distant occupations. There are three requirements for a “job map” to be useful. Firstly, a distance between two occupations implies qualitative similarity between the two occupations in terms of tasks performed and skills required. Second, a corollary to the first, a distance between two occupations implies the cost associated with job change from one occupation to the other. Finally, as a result of the first two, various economic indicators and demographic attributes of occupations projected on the job map form spatial patterns. If these three are met, then the job map can be used and analysed in much the same way as the conventional maps.

Section 2 describes a method of creating a job map. A gravity model used to predict patterns of geographical mobility based on physical distances is applied in a reverse way to measure similarities between pairs of occupations from a matrix of job changes. Multidimensional scaling (MDS) can then be applied to the matrix to restore the coordinates of occupations. MDS is a method for reducing the dimensions of the relationships among objects represented in a multidimensional space while retaining the topology between objects as much as possible. If the number of dimensions can be reduced to two or three, the relationships between occupations can be examined visually. An output will be a job map that places similar jobs close together and dissimilar jobs far away apart. Section 3 presents a job map for UK SOC2000 minor occupation groups that classifies jobs into 81 categories, based on data from the British Quarterly Labour Force Surveys 2001-05.

Once occupations are projected onto a map, further geographical analysis becomes possible. Labour market variables by occupation plotted on a map generally show spatial autocorrelation: a value for an occupation is similar to the values of the proximate occupations. This is not surprising, provided that the map is properly constructed, because nearby occupations are similar. Similar occupations face similar economic circumstances and occupational mobility should act to smooth out the differences. The existence of spatial autocorrelation allows a surface of a variable covering the multidimensional space of jobs to be interpo-
lated. In section 4 labour market variables such as wage, unemployment, and vacancies are estimated for a spectrum of jobs, using spatial statistical methods and the Geographical Information System. Visual inspection of patterns of labour market variables enables identification of a group of jobs with higher demand, higher wages, or growing employment.

Section 5 describes occupational mobility between jobs as well as entrance and exit from the labour market using the job map. Section 6 summarizes the article’s findings and discusses the prospects for using the job map to analyze occupational labour markets and occupational mobility.

2. Theory and method

2.1. Occupational mobility and geographical mobility compared

Although geographical mobility has attracted more attention than occupational mobility, there are many logical equivalents between the two. The labour market is partitioned into many submarkets, by geography and by type of required skill. There are barriers to mobility across labour submarkets, and immobility of labour engenders disparities in unemployment and earnings across submarkets. The main barriers are costs to mobility and incomplete information. In the case of geographical mobility, both costs to mobility and incomplete information increase with distance from one regional labour market to the other. The same can be said about occupational mobility; barriers to mobility should be greater between dissimilar jobs and less between similar jobs. Costs to occupational mobility include investment in occupation-specific human capital and the sunk cost of previous investment in occupation-specific human capital if the acquired skills are abandoned after the job change. Such costs will be smaller if the skills required in an occupation can be transferred to another occupation. Similarly, incomplete information should be less serious between similar jobs.

Whereas the physical distance between regional labour markets can be readily measured on a map, similarity between occupations is not usually available. One approach to measuring this “distance” would be to survey a range of occupations on skills required and tasks performed in order to identify similarities between occupations based on common skills and tasks. However, skills and tasks are also categorical and are difficult to relate to each other.

The approach taken here is to use the pool of experiences of those who changed jobs in the past. Frequency of job changes across occupations, with appropriate adjustments, gives a measure of similarity between occupations. The rest of this section describes a method to measure similarities between pairs of occupations based on an analogy with the gravity model used in studies of geographical mobility. While the matrix of similarities itself describes the relationships between occupations, it is not readily comprehensible. Therefore, multidimensional scaling is applied to the similarity matrix to enable the relationships between occupations to be visualized.
2.2. The gravity model and the derivation of a measure of similarity between occupations

In a classical gravity model for migration, a flow from locations \( i \) and \( j \) is modelled as being proportional to the sizes of origin and destination and inversely related to a distance between the two locations:

\[
M_{ij} = \alpha P_i P_j f(d_{ij})
\]  

(1)

where \( \alpha \) is a constant associated with overall mobility; \( P_i \) and \( P_j \) are the population sizes of origin and destination, respectively; and \( f(d_{ij}) \) is an inverse function of distance between the two locations.

Since in a spatial case, \( d_{ij} \) and \( d_{ji} \) are exactly the same, there will be no net migration between the two locations. Therefore, the gravity model in this formulation can be seen as depicting random flows that occur under equilibrium, where no net migration exists.

In empirical analysis of geographical mobility where net migration does occur, the gravity model is usually augmented with generalized push and pull factors so that regional economic variables can be incorporated in the migration equation as determinants (Molho 1986).

\[
M_{ij} = \alpha P_i P_j f(d_{ij}) \times A_i B_j
\]

(2)

where \( A_i \) is the push factor of the origin and \( B_j \) is the pull factor of the destination. Both push and pull factors take positive values and are functions of explanatory variables of each location. In order to maintain consistency with equation (1), both should be calibrated so that their average across locations equals unity.

The gravity model for spatial mobility can be used to model labour flows between occupations by replacing the population sizes of regions with employment sizes of occupations and the function of distance with a measure of similarity between two occupations. The justifications for doing so are that flows between occupations are strongly skewed (i.e., most flows occur between certain pairs of occupations) and flows between a pair of occupations are nearly symmetric (i.e., flows to and from a pair of occupations are nearly equal). In the case of spatial mobility, distances are measured exogenously; the task here is to derive similarity between pairs of occupations from the origin and destination matrix of flows between occupations.

Define mobility between two occupations as:

\[
m_{ij} \equiv \frac{M_{ij}}{P_i / P_j}
\]

(3)

This definition standardizes a flow of occupational change \( (M_{ij}) \) by employment at risk \( (P_i) \) as well as the share of employment of destination \( (P_j) \) to total employment \( (P_i) \). The variable so defined is similar to a measure known as migration velocity (Rees et al. 2000), and is consis-
tent with conventional measures of mobility for outflow, inflow, and total mobility:

Outflow rate: \( m_i = \frac{M_i}{P_i} = \frac{M_i}{P_i} \)
Inflow rate: \( m_j = \frac{M_j}{P_j} = \frac{M_j}{P_j} \)
Total mobility: \( m* = \frac{M*}{P*} = \frac{M*}{P*} \)

With this measure of mobility, the augmented gravity model can be rewritten, with a minor adjustment in the constant as:

\[ m_{ij} = \alpha \times A_i \times B_j \times f(d_{ij}) \] (4)

Mobility between two occupations is the product of a constant depicting overall mobility, the push factor of the origin occupation, the pull factor of destination occupation, and a measure of similarity between the two occupations.

In order to derive similarities between pairs of occupations, push and pull factors should be specified with exogenous variables, and parameters should be estimated empirically. Such an approach, which requires full scrutiny of the mobility equation, is beyond the scope of this article. Instead, a pragmatic solution to obtain a proxy for similarity is introduced.

The mobility between occupations can be decomposed into overall mobility, relative outflow rate from the origin, relative inflow rate to the destination, and a residual term:

\[ m_{ij} = m* \times m_{ij} \times m_{ij} \times m_{ij} \] (5)

The residual term indicates the strength of the association between a pair of occupations. Comparison of equations (4) and (5) suggests that the last term in equation (5) is the measure of similarity between occupations:

\[ f(d_{ij}) \approx \frac{m_{ij}m*}{m_{ij}m*} \] (6)

Since actual mobility is subject to various barriers including (dis)similarities between occupations, both push factors approximated with outflow rates and pull factors associated with inflow rates are underestimated. However, since the underestimations are present in all measures of mobility on the right-hand side of equation (6) in a similar way, the underestimations will cancel one another out. Serious problem may exist in differences in the margins of errors of similarity between similar and dissimilar occupations.

2.3. Creating a job map using multidimensional scaling

Multidimensional scaling (MDS) is a method that represents measurements of similarity between pairs of objects as distances between points in a low-dimensional multidimensional
(often two-dimensional) space, making the data accessible to visual inspection and exploration (Borg and Groenen 2005). By deriving a measure of similarity from the job change data, it is possible to restore the coordinates of occupations that can be mapped to show the relationships among occupations.

Based on the preceding discussion, define a matrix of similarity between occupations i and j as follows:

$$s_{ij} = \frac{m_{ij}m_{ji}}{m_{ij}m_{ji}}$$

Two occupations are more similar the greater the mobility between them (controlled for the total outflow and inflow rate); this measure can be calculated from the latter expression. Although the similarity matrix is often nearly symmetric, it is not exactly so. This is problematic if projection onto a map is intended, as the distance to and from two locations should be identical. Therefore, the following decomposition is made:

$$s_{ij} = \left| \frac{1}{2}(s_{ij} + s_{ji}) \right| + \frac{1}{2}(s_{ij} - s_{ji})$$

The first matrix on the right-hand side is the symmetric component; it is used to define the multidimensional space and is mapped by applying MDS. The second matrix is the asymmetric component, indicating that a change from one job to another is less costly than a change in the reverse direction. There are at least two reasons for asymmetry, both of which are associated with the level of skill. The first reason is the cost of training in acquiring skills when moving to a more skilled job. An individual knowing more advantageous conditions in another occupation would not change job if the cost of training is greater than the gain from the job change. The second reason, a mirror image of the first, is the cost of realizing the sunk cost of previous investment in human capital that occurs when moving to jobs that do not require already-acquired skills. Individuals in a highly skilled occupation might stick to a job unless an opportunity for a better job appears; in the case of job loss, they might remain unemployed and wait rather than change jobs, or they might retire. This asymmetry is not likely to be present between a pair of occupations with different skill content at the same skill level.

Asymmetry distinguishes occupational mobility from geographical mobility. It is preferable that this asymmetry be included in the job map. If occupations can be laid out on a two-dimensional plane from the symmetric component of the similarity matrix, the asymmetric component can be assigned to the third (lateral) axis (note that asymmetric component is symmetric when the absolute of the elements are taken). Plotting the symmetric component on the x-y plane and the asymmetric component on the z axis (probably expressed with contour lines) would create an intuitive graphical representation showing that going uphill is harder than going downhill. However, to make such representation, the relationship among occupations in the asymmetric component should follow the transitive law; for a visually pleasing outcome
the order should be spatially continuous.

In the British case examined in the next section, the similarity matrix is very symmetric, possibly because the two reasons for asymmetry offset each other. It is not possible to distinguish the training cost and the sunk cost of occupational mobility by the job data alone. For this reason, the idea of assigning the asymmetric component to the third axis is set aside in the rest of this article.

3. Creation of job maps from British data

3.1. The data

The results of the British Quarterly Labour Force Surveys (QLFS) are used to create a job map. The QLFS asks respondents about employment at and one year before the survey date, from which an occupation at both ends of one-year period can be obtained. Occupational changes are tabulated to create origin and destination (OD) matrix of job change counts between all occupation pairs. Five spring series of the QLFS for 2001-05 are compiled to tabulate the OD matrix of occupational change, because such changes are relatively rare and single-year tabulation does not produce enough observations for wide range of occupation pairs, especially when finer classification is used. Since the interest here is the intrinsic relationships between occupations, compilation of data for several years also removes the temporal labour market fluctuations affecting occupation changes. The classification of occupations is based on SOC2000, which classifies occupation into 9 major groups, 81 minor groups, and 353 unit groups (Office for National Statistics 2000).

Table 1 breaks down the working population by occupation one year before the survey to show the aggregate flows between occupations. Of 25 million working population, 12% held a different job by the end of the year. Multiple job changes within a year are not taken into account in the tabulation. The QLFS asks whether a respondent changed occupation in the past 12 month before asking the previous occupation, so there is no overcounting of job changes as a result of miscoding of the same occupation into similar occupations, as was the case in the U.S. Panel Study of Income Dynamics data (Parrado et al. 2007; Kambourov and Manovskii 2008). Considerable occupational changes occur between unit groups; changes between larger occupation groups are less frequent. Net flows between occupations are only about a tenth of gross flows, because flows occur in both directions for a pair of occupation groups and each occupation group sends and receives flows in an offsetting fashion.

Occupational changes are cross-tabulated by current and previous occupation for those who are both working at the end of the one-year period and changed occupation; job changes that involved non-employment at either end of the one-year period because of unemployment, retraining, education, or any other reason for inactivity are not included in the tabulation. Initially, an OD matrix of occupation changes between 353 unit groups was attempted. It produced an extremely sparse matrix, however, with many unit groups recording no job changes to
other unit groups. The creation of a job map for 81 minor groups was therefore attempted.

### 3.2. The job map

After the OD matrix of occupation changes is tabulated between SOC2000 minor groups, the similarity matrix is calculated and the symmetric component of the similarity matrix used to perform nonmetric MDS. Two-and three-dimensional solutions are obtained, with $R$-squared measures of 0.893 and 0.928, respectively. The coordinates of occupations for two-dimensional solution are mapped in Figure 1, with points representing each occupation. Similar occupations are placed close together and dissimilar ones far apart. Frequent job changes can be expected between proximate occupation points. The numbers in the figure are the SOC2000 codes. The two-dimensional space is divided into Voronoi polygons that delimit space to the nearest occupation point.

The two axes in the map can be interpreted in a similar fashion to principal components (Cox and Cox 2001). The horizontal axis is associated with the skill level, with Professional and Managerial occupations located to the right and Elementary and Personal Service occupations to the left. The vertical axis is associated with skill content, with manufacturing-related occupations at the top and service-related occupations at the bottom. This axis is also strongly associated with gender. Note that movement along the vertical axis also involves training costs, because the skills required are qualitatively different.

Since MDS squeezes what is really a multidimensional space into a two-dimensional space, some similarities are over- or underrepresented. For severe cases of underrepresentation, an arc is added to show that a pair of occupations is more proximate than is shown on the map; an arc is analogous to a “highway” of occupational mobility. Since there are two distances between two occupations, an arc is drawn whose curve represents the direction; an arc curving to the right shows the movement toward an occupation. Many “highways” occur between

### Table 1: Flows between occupations, annual average 2001-05

<table>
<thead>
<tr>
<th>Change since 1 yr ago</th>
<th>Gross flows (% of working)</th>
<th>Net flows (% of working)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Changed occupation$^a$</td>
<td>3,071,070 (12.0%)</td>
<td>—</td>
</tr>
<tr>
<td>between Major Groups</td>
<td>1,484,091 (5.8%)</td>
<td>113,661 (0.4%)</td>
</tr>
<tr>
<td>between Minor Groups</td>
<td>1,856,210 (7.3%)</td>
<td>178,623 (0.7%)</td>
</tr>
<tr>
<td>between Unit Groups</td>
<td>2,017,547 (7.9%)</td>
<td>226,803 (0.9%)</td>
</tr>
<tr>
<td>within Unit Groups$^b$</td>
<td>1,053,523 (4.1%)</td>
<td>—</td>
</tr>
<tr>
<td>Stayed put</td>
<td>20,285,630 (79.6%)</td>
<td></td>
</tr>
<tr>
<td>Previously unemployed</td>
<td>457,238 (1.8%)</td>
<td></td>
</tr>
<tr>
<td>Previously inactive</td>
<td>1,678,019 (6.6%)</td>
<td></td>
</tr>
<tr>
<td>Working total</td>
<td>25,491,957 (100.0%)</td>
<td></td>
</tr>
</tbody>
</table>

$^a$ Occupational changes at different levels of occupation groups do not add up to this figure
$^b$ Number of those who changed employer but in the same unit occupation group

Source: QLFS Spring series 2001-05
Figure 1  Job map for SOC2000 minor groups
Points represent occupations and the numbers are UK SOC2000 minor group codes.

Source : QLFS Spring series 2001–05.
occupations with the same skill content at different skill levels, often in both directions (examples include movement to and from protective service occupations (331) and protective service officers (117)). There are also one-way highways, such as movement from legal associate professionals (352) to legal professionals (241), indicating that demotion is rare in the legal profession. Some unexpected associations also exist, such as movement to and from managers in farming (121) and science professionals (211). Inspection of the original record reveals biologists and biochemists (2112) becoming farm managers (1211) and managers in animal husbandry, forestry, fishery, etc. (1219) and vice versa. The last example exemplifies an aggregation problem even among minor occupation groups.

The multidimensional space of relationships between occupations fits into a two-dimensional map reasonably well, revealing a broad view over a range of occupations. Some accuracy is sacrificed, however. Cartographic expressions can be used to supplement some of the information lost in the fitting process.

4. Cartographic analysis

4.1. GIS and spatial statistical methods to describe characteristics of occupations

Visualizations of economic and demographic variables for each occupation on the job map will also help conceptualize various occupations. GIS can be used for such tasks as visualizing (or mapping) data, integrating data from various sources, and performing spatial statistical analysis. Attributes of occupations on a map generally show positive spatial autocorrelation (i.e., attribute values of proximate occupations are positively correlated). The existence of spatial autocorrelation means that a recognizable pattern emerges when the variable is plotted on the map. Since viewing a pattern is more intuitive than examining variables independently for each occupation, mapping the attributes of occupations helps users understand the economic situation an occupation or a group of similar occupations is facing. Mapping occupational attributes is also useful for job-seekers, who can use the job map to navigate through the plethora of jobs in search of growing or better-paid jobs.

Spatial autocorrelations of labour market and other variables for occupations on the job map emerge because (1) similar jobs face similar economic and demographic situations; and (2) similar jobs interact with each other through occupational mobility. Table 2 lists spatial autocorrelation (Moran’s I) for selected variables plotted on the job map. Since the choice of spatial structure is somewhat arbitrary, spatial autocorrelation were measured using three alternative spatial structures; (1) contiguity defined by direct links of Delauney triangulation; (2) inverse distance between the occupation coordinates; and (3) the similarity matrix defined in section 2. While differences exist depending on which spatial structure is used, most variables have statistically significant positive spatial autocorrelation, demonstrating that the job map is revealing the pivotal components of occupation structure and probably the underlying occupation mobility. Fewer statistically significant spatial autocorrelations when inverse distance is used
compared to when contiguity is used suggests that the job map represent the topology of the relationships between occupations relatively well but not so much of distance. Nevertheless, the fact that non-labour market variables such as proportion of workers having any health problems or rate of owner-occupation suggest that the job map can be used to analyse various social and socio-economic issues associated with occupations.

4.2. Employment and employment growth

Figure 1 ignores the size of employment in each occupation. Employment sizes can be shown by a proportional symbol or by defining employment densities per area on the map. Five distinct domains of high density are shown in Figure 2(a) which may be labelled ‘personal services and retailing’ (lower left); ‘factories and transport’ (upper left); ‘engineering and telecommunication’ (upper right); ‘advanced services’ (centre); and ‘administrative–managerial continuum’ (lower right).

Growth in employment can be shown in many ways, here it is shown as a continuous surface. Average annual employment growth during the five-year period 2001–05 for each occupation is spatially interpolated to create a surface using a spatial regression method known as kriging (Wackernagel 2003). A virtue of using kriging is that it suppresses sampling error by taking account of the values of proximate jobs. Moreover, it allows inspection of the employment growth of undefined jobs that fall between defined categories. The map shows a centre of growth at a location surrounded by legal associate professionals (352), research professionals (232), and artistic and literary professionals (341). Current employment in that location is not

Table 2  Spatial autocorrelation: Moran’s I (s.d. in parentheses) for selected variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>Contiguity</th>
<th>Inverse distance</th>
<th>Similarity matrix</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employment growth</td>
<td>0.144(0.063)*</td>
<td>0.033(0.042)</td>
<td>0.234(0.043)**</td>
</tr>
<tr>
<td>Net weekly wage (average)</td>
<td>0.537(0.063)**</td>
<td>0.145(0.042)**</td>
<td>0.336(0.043)**</td>
</tr>
<tr>
<td>Unemployment rate</td>
<td>0.307(0.061)**</td>
<td>0.104(0.040)**</td>
<td>0.332(0.041)**</td>
</tr>
<tr>
<td>Unfilled vacancy per employment</td>
<td>0.160(0.062)**</td>
<td>0.022(0.041)</td>
<td>0.195(0.042)**</td>
</tr>
<tr>
<td>Long term unemployment (1yr or more) rate</td>
<td>0.334(0.061)**</td>
<td>0.127(0.040)**</td>
<td>0.344(0.041)**</td>
</tr>
<tr>
<td>Length of employment (average)</td>
<td>0.136(0.063)*</td>
<td>0.045(0.042)</td>
<td>0.272(0.043)**</td>
</tr>
<tr>
<td>Age (average)</td>
<td>0.050(0.063)</td>
<td>0.039(0.042)</td>
<td>0.070(0.043)</td>
</tr>
<tr>
<td>Male rate</td>
<td>0.589(0.064)**</td>
<td>0.180(0.042)**</td>
<td>0.350(0.043)**</td>
</tr>
<tr>
<td>Non-white rate</td>
<td>0.064(0.062)</td>
<td>0.014(0.041)</td>
<td>0.188(0.042)**</td>
</tr>
<tr>
<td>Part-time rate</td>
<td>0.511(0.063)**</td>
<td>0.157(0.042)**</td>
<td>0.243(0.043)**</td>
</tr>
<tr>
<td>Health problems rate</td>
<td>0.313(0.063)**</td>
<td>0.091(0.042)*</td>
<td>0.249(0.043)**</td>
</tr>
<tr>
<td>Higher education (first degree or more) rate</td>
<td>0.409(0.064)**</td>
<td>0.130(0.042)**</td>
<td>0.488(0.043)**</td>
</tr>
<tr>
<td>Owner–occupier rate</td>
<td>0.463(0.063)**</td>
<td>0.112(0.042)**</td>
<td>0.303(0.043)**</td>
</tr>
</tbody>
</table>

Notes: Levels of statistical significance at 1% (***) and 5%(*) ; expected index for 81 observations is –0.0125.
Sources: QLFS Spring series 2001–05 and NOMIS.
substantial but is growing; a new job (or category) is likely to emerge that links the large separate domains of ‘advanced services’ and the ‘administrative-managerial continuum’.

4.3. **Wages, unemployment, and vacancies**

Labour market conditions are needed to fully describe the status of various occupations. Wages and unemployment rates by occupation are calculated from the QLFS 2001–05; rates of unfilled vacancy by occupation are obtained from NOMIS (https://www.nomisweb.co.uk/) based on vacancies notified to Jobcentres. The values are again interpolated using kriging to form a surface (Figure 3).

![Figure 2 Job map showing employment and employment growth](source: QLFS 2001-05)

![Figure 3 Wages, unemployment, and unfilled vacancies](source: QLFS Spring series 2001–05 and NOMIS)
Wages by occupation have a clear lower-left to upper-right gradient, partly related to the level of skill. Movement on the map involves costs, some of which may be retrieved if the job change movement is toward the upper right. Unemployment and vacancy rates show similar patterns, with low-skilled occupations showing high rates of both unemployment and vacancies. Unemployment and vacancies can be combined to estimate excess/shortage of labour at prevailing wage for each occupation, but that is not done here because under-enumeration of vacancies in skilled occupations is very likely with the data used.

It is possible to relate map distance in terms of monetary cost for job change if we could estimate equilibrium wages across occupations, i.e. wage differentials that just compensate for the job change costs. The distributions of employment growth (Figure 2(b)) and unemployment and vacancy rates all suggest systematic labour shortage in skilled occupations (in the right on the map) and thus the prevailing wage cannot be approximated with the equilibrium wages.

5. Analysis of occupational mobility

Having mapped jobs, identified growing occupations, and obtained some indicators of labour market conditions, it is now possible to examine occupational mobility. There are three types of occupational mobility: entry into employment, job change across occupations, and exit from employment. The second type, movement between occupations, is discussed first.

Inflow and outflow rates for each occupation show very similar patterns, despite the fact that they do not include movements within minor occupation groups. The strong correlation between inflow and outflow is another similarity with geographical mobility. Gross mobility is more closely related to turnover; it is thus more useful to view mobility by turnover and net mobility than by inflows and outflows (Fig. 4).

Gross flows between pairs of occupations are displayed with an underlay showing the net mobility to each occupation (Figure 5). Because there are two directions in flows between two points, arcs are drawn so that the flow turns to the right. Prominent flows are evident from sales assistants and retail cashiers (711) to administrative occupations and managers in distribution, storage and retail (116) (in the lower right). These flows are especially pronounced because occupation 711 has a relatively large employment base and is an entry-level occupation (discussed below). The upward convex arcs in Figure 5 are generally more pronounced, meaning that the dominant flows are from the left to the right, representing career upgrading and increases in income.

For mobility in and out of employment, it is difficult to determine whether the movement is a temporal or a permanent one. Only some of the examples of entrance to and exit from employment are shown in Figure 6. School leavers, many of whom are first-time entrants, enter the labour market largely through a handful of entry-level jobs in elementary and low-skilled jobs. In comparison, outflows to retirement, most of which are permanent, emanate
from more diverse occupations. Therefore, occupational mobility over the life cycle can be grossly summarized as follows: entry into the labour market through a small number of entry-level occupations, followed by some proportion of workers succeeding in upgrading their careers through occupational change, eventually followed by retirement at various goals of career.

6. Conclusion

In an attempt to understand the relationships among occupations, this article defines a measure of similarity of pairs of occupations based on the gravity model. The similarity matrix for British SOC 2000 minor occupation groups is derived from an origin and destination matrix of occupational change tabulated from the QLFS 2001-05 datasets. Multidimensional scaling is then applied to the similarity matrix to produce a “job map”. Similarity of occupations can be fairly well represented in a two-dimensional space in which the primary axis is associated with the skill level and the secondary axis is associated with the skill content. The job map allows individuals to identify pairs of occupations within which it is relatively easy to change jobs and to use the job map to navigate a career path.

Various economic indicators and demographic attributes by occupation generally showed spatial autocorrelation when projected on the job map, and spatial patterns emerged. Because a spatial pattern is more readily comprehensible than a variable treated independently for each occupation, spatial patterns are drawn on the job map using a spatial statistical method and the Geographical Information System. This allowed identification of growing jobs, demanded jobs, and highly rewarded jobs.

Occupational mobility, including job changes and entrance and exit from the labour market,
are represented visually, and the general pattern of mobility and the life-cycle aspect of occupational changes are described. The stylised descriptions are that (a) entrance into the labour market occurs through a limited number of entry-level jobs, most of which are elementary or low skilled jobs; (b) the dominant direction of occupational change is toward career upgrading; and (c) the rate of retirement is roughly equal across occupations.

Although the subject under study is non-geographical, it has been possible to apply the “first law of geography” in the analysis of occupations. With the use of job map, occupations can be examined in much the same way as geographers use maps to investigate geographical problems. In several respects, the use of a map is more useful or needed for analyzing occupational labour markets than it is for analyzing geographical labour markets. First, the axes of the job map are associated with two principal properties of occupations, skill level and skill content. Therefore, the direction of occupational change will have direct implications for the type of move; i.e., whether the move upgrades one’s career or sacrifices some of the occupation-specific human capital acquired in the previous occupation. Second, reorganization of standard occupation classification occurs more frequently, but the job map recognizes occupations that
fall in between defined categories. This allows occupations to be analyzed even if the classification scheme changes, provided that some information that links between the old and the new categories is present. Consistent analysis of occupations over time can be conducted through spatial aggregations on the job map. Third, the spatial patterns of geographical mobility cannot be directly compared across countries but that of occupational mobility on the job map can, if the axes of the job map for each country represent common components across countries. Geometrical transformation of job maps for each country, based on some equivalent occupations in different classification schemes, allows direct comparisons of mobility patterns.

Many of the practical problems encountered in empirical studies of occupations are associated with identification of occupations. Job map coupled with spatial statistical methods provide one way to solve such problems.

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