WORKING PAPER 502

SYNTHETIC DATA GENERATION AND THE EVALUATION OF URBAN PERFORMANCE: A LABOUR MARKET EXAMPLE

M. BIRKIN AND G.P. CLARKE

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School of Geography
University of Leeds
Leeds LS2 9JT

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1. INTRODUCTION

One of the products of the 'computer revolution' of the 1980s has been a data explosion, giving rise to an incredible richness of available statistics on the urban and regional economy. Careful inspection and manipulation of data such as these can obviously yield insights into the structure of the urban system. For example, there is plentiful data on the local labour market, which forms the subsystem of interest in this paper. Section 2 provides a discussion of the available data, and presents a preliminary picture of the city of Leeds which can be extracted directly from these sources.

Our next concern is how such a very rich data base can be effectively converted into a true 'information system' - basically, a system which provides answers to meaningful questions about the way in which the system in question functions as an organic entity. We would argue that at least three types of addition are necessary to effect this transition from 'data base' to 'information system', and these additions provide the basic structure to this paper.

The first type of weakness which we will consider is inter-dependence between attributes. The problem here is one of establishing linkages within and between data sets. For example, in the British census we may know very detailed information about the distribution of person-types (eg occupation groups) in space. Furthermore, from national data, we know a lot about the income generation capabilities of such different income groups. What we do not know is the spatial pattern of income distributions, and this is where linkage between the two types of data set is required.

In another example, we may know the age-sex split in a zone of the city, and as we have seen, we know the occupational structure, so what can we say about the occupational structure within different age groups within different zones? In this case, we need to establish linkages within a data set.

In Section 3 of the paper, we will argue that linkages such as those discussed above can be efficiently and effectively established using the technique of microsimulation. The system also provides us with an efficient and flexible accounting base. The need to establish links such as these is increasingly important in both the public and private planning contexts, in view of increasing social differentiation and fragmentation. In the welfare context, we need to identify particular groups, like the unskilled, under-educated, unemployed, or lone parent families, and aggregate measures simply may not be good enough. Similarly, in the private planning arena, it may be necessary to isolate particular segments of the market for targetted advertising, capital investment, and so forth.

A particular kind of interdependence is spatial interdependence. This can also be looked at as a method of establishing missing links between the supply- and demand- sides of the economy. Of course, it is important to establish these links for both kinds of sector. Hence, for residential zones we may want to know something about the availability of, and accessibility to, job opportunities, and the effects of expansion or, more likely, contraction in that set of opportunities. On the supply-side, we begin to understand the role of individual organisations or sectors in the pattern of provision of jobs and of commodities.

The technical aspects of spatial interdependence can be embraced using a well-known set of spatial interaction models. The procedures are made slightly more complicated, but also much more effective, by the availability of the sectorally disaggregate, micro-simulated data base. This step in model construction is reviewed in Section 4.

Having established the links between the supply- and demand- sides, we are now in a much more effective position to try and make some sense of the functional relationships within our system of interest. The problem is conceptualised through the adoption of a suite of performance indicators. These measures may be thought of as a set of outputs from the information system of Sections 3 and 4. In view of the flexibility of the information system, the set of outputs which may be defined is also both flexible and diverse. Section 5 therefore provides both a guide to useful indicators, and an evaluation of economic performance using such indicators for the city of Leeds.

The third aspect of our information system is dynamics. In this context, we need to distinguish between short- and long-term forecasting. Although the arguments about long-term forecasting with respect to dynamics, structural change and bifurcation theory are well-rehearsed, the principal advantages offered by the framework we have presented here relate to short-term forecasting. One aspect of this is old-fashioned impact analysis. The information system and evaluation package we have presented provides an immensely powerful tool for assessing the immediate impacts of changing structures or parameters within the system. This is reviewed in Section 6.

A second aspect of short-term forecasting is updating. Obviously a major weakness of many existing databases like the census is that they are static, cross-sectional snapshots of ever-changing structures. For example, since the last census in Britain in 1981, we are aware of major changes, including sales of council housing, increasing unemployment, and crises in local government organisation and service provision to name but a few. Together with possible specific local aspects (eg industrial estates, new housing,...), these factors combine to make constant updating of existing databases highly desirable. Updating remains a crucial feature step within the system outlined here. This, and other aspects of ongoing model design, are also discussed in Section 6.

2. LOCAL LABOUR MARKETS - EXISTING DATA SOURCES

Before sketching out the components of the model-based information system, and its potential for measures of impact and performance, it is useful to briefly review existing data sources available for local labour markets. It is not the aim here to provide a full review of intra-urban industrial geography (cf Bull 1985, Hasluck 1987), but to concentrate on the benefits and limitations of principal data bases. For each of the main source types, an example for the Leeds economy will also be provided. Fuller details appear in Clarke G. (1987).

2.1 Census of Employment

The Census of Employment has probably been the most widely used of any single source since it provides the most accurate sectoral information on local labour markets. It is based on a compulsory and detailed survey of all firms registered for PAYE schemes with the Inland Revenue, and its availability through the National On-line Manpower Information System (NOMIS) has considerably aided accessibility. The major drawback with the Census of Employment is the fact that the smallest area information available is for Amalgamated Office Areas (AOAs), which are only aggregations of Employment Office Areas. Consequently, the Census has found most use in regional studies of employment change (i.e Fothergill and Gudgin 1982, Townsend 1986) and for studies of larger Metropolitan areas (i.e Lever and Moore 1986 for Glasgow, Palmer 1986 for West Yorkshire). The eventual appearence of the 1984 statistics will undoubtedly help add another chapter to regional industrial change, in light of the recent major recession.

For a city the size of Leeds, 9 AOAs are available for analysis. Fig. 2.1 shows the change in male, female and part-time female employment for each AOA between 1971 and 1981. The interesting feature here is the growth in all employment categories for the outer districts and the decline in the full-time male and female employment totals for the inner AOAs of City and Bramley. In stark contrast, the growth in part-time female employment clearly stands out for all areas of the city. More details on sectoral change appear in the next section.

2.2 Census of Population

The 1981 Census of Population provides a wealth of information useful for the analysis of local labour markets. It remains the chief source for the detailed characteristics of the local employed population which forms the heart of the residence base of the micro-simulation study here (see section 3). On the facility side, the 10% workplace statistics provide a sample of the number of people working in a zone. A comparison of these residence and work-based population totals allows a preliminary picture of 'job mismatch'; the number of jobs in a zone as a percentage of the number of employed residents in that zone. This idea of mismatch is illustrated for all person types in Fig 2.2

and for selected wards in Figs 2.3(a-c). Fig 2.3a shows North, a wealthy residential outer suburban area, where the majority of the population work outside the locality; Fig. 2.3b shows Richmond Hill, an inner industrial area, where the ratio of jobs to people is much higher, especially in the manufacturing sector; Fig. 2.3c shows Harehills, the ward with the worst unemployment rate in the city, which has relatively few jobs and consequently high out-flows (see map in Fig 2.2 for ward locations). These ideas of mismatch will be explored in greater detail using interaction data in section 4 .

The 10% workplace data also allows a more spatially disaggregate picture of sectoral employment distributions than the Census of Employment (although we should keep in mind the sample size). Figs. 2.4-2.6 show the distribution ofjob types in the three wards chosen above.

2.3 Directories

Although the ward-based Census information provides much of the data for the simulation study which follows, it is important to stress that the information system we advocate eventually needs to be disaggregated to the level of major firms within particular enumeration wards. The availability of a number of industrial directories enables a great deal of firm-based information to be compiled. The major sources used elsewhere include Dun and Bradstreet, Industrial Market Location Directories, Factory Inspectorate Data and V.A.T. returns (particularly useful for information on small firms). Each of these have particular strengths and weaknesses, and Foley (1983) concludes that it is dangerous to rely on any one of these alone. Clarke (1987) has compiled an inventory of firms in Leeds using three of the above sources (plus miscellaneous directories and local company reports) which will eventually form an input into the modelling exercise. Figs 2.7-2.8 show two examples of the type of information gleaned so far-the spatial distribution of firms employing more than 150 persons and the number of firms starting business since 1970 (as a percentage of the total number of firms). The areas of heavy employment are clearly emphasised in Fig 2.7 whilst the distribution of new firms (although most employ less than ten : see Clarke 1987) show a marked suburban bias in Fig 2.8. (It is interesting to compare the rate of new firm formation shown in Fig 2.8 with the Census of Employment data seen in Fig 2.1).

2.4 Summary: the need for interaction data

The brief review of local data sources has helped to highlight the sort of data currently available from secondary sources. Although all of these sources are useful in determining the characteristics of local labour markets, especially in labelling areas 'work-based' or 'residential', 'manufacturing' or 'service', they offer little insight into the zonal interdependencies and the degree of commuting for different social groups and industry types. A long history of studies have shown how commuting patterns differ between various socio-economic groups (usually by mode of transportation), but few studies have actually attempted to model the connections between residence and workplace zones, and how these vary across the attributes of the population. As Cheshire (1979) and Gordon and Lamont (1982) stress, it is vital to show how localised job creation, in areas of apparent decline, affect unemployment levels in that area rather than merely the balance of migration and commuting flows. The latter have become increasingly important over recent years as the affluent have moved outwards and the less well-off have been imprisoned in inner areas, their mobility constrained by perceived uncertainty and difficulties of finance (Gordon 1985). This will be taken up again in section 5.

3. SYNTHETIC MICRO-DATA GENERATION

The technique of 'micro-analytic simulation modelling' has attracted increasing interest in the economic literature since the pioneering work of Orcutt et al (1961). More recently still, original and potentially exciting applications have begun to appear in the context of urban land-use and transportation modelling (eg McFadden et al, 1977; Kain and Apgar, 1978, 1985; Clarke and Holm, 1987). In this section, we wish to try and clarify the nature of the micro-analytic approach, and to examine some of the reasons for its increasing popularity. The features of our own micro-level data-base, known as 'RUIN', are described towards the end of the section.

It is well-known that one of the most enduring and least tractable problems of economics, and particularly spatial economics, is the so-called 'aggregation problem' ie a method of problem-solving which is mutually consistent at both the micro- and meso- or macro- levels. The application of micro-simulation methods may usefully be thought of as a direct attack on this problem. The basis of the method is an explicit representation of the attributes of individual actors within an economic subsystem. Where a macro-level process, such as market clearing, is to be represented, then it is a straightforward matter to aggregate lists of individuals into bundles appropriate for the model in question. We also assume that it is possible to derive methods which then feed back the results of the macro-level process to the micro-level (cf Birkin and Clarke, M., 1986).

In countries where micro-simulation models are now popularly used (notably the USA and Sweden) primary micro-data sources are typically available, for either a completely enumerated or sample population. Appropriately specified dynamic models permit the characteristics of this sample population to be projected forward over time, and techniques defined for the outcome of the process. If these outcomes are compared under alternative forecasting scenarios, then policy implications can be derived, and this constitutes the most common application of the methodology. In addition to its relationship to the aggregation problem, a major advantage of the approach is that it permits the treatment of a high degree of heterogeneity in the data set ie the representation of the system as lists of individuals facilitates greater disaggregation than in the corresponding meso-level or occupancy matrix approach (cf Clarke, 1981; Kain and Apgar, 1985, Appendix A).

It has been argued elsewhere (Birkin and Clarke, M., 1986) that the twin advantages of flexible aggregation and the representation of interdependence, offer a powerful argument in favour of micro-simulation models as an alternative solution method for problems which are usually specified at the meso-level. This means that it may be desirable, as we shall argue in subsequent sections of this paper, to consider the application of a micro-analytic simulation methodology even when primary micro-data is not available, as is generally the case in the United Kingdom. To make progress here, what we need to do is to generate our micro-data synthetically. The way in which this can be done is described in further detail elsewhere (Birkin and Clarke, M., 1987) where a set of methods is described which ensure that the synthetic data set exhibits characteristics which are consistent with known aggregate distributions.

In comparison with certain other micro-simulation models, the RUIN data base developed at Leeds has a relatively sparse list of attributes, comprising seven kinds of individual attribute, and a further five household attributes (see Table 3.1) (compare for example the Micro-Analysis of Transfers to Households - MATH - model, with circa 50 family or household attributes, and over 200 individual characteristics, eg Beebout, 1980). However certain positive features of the RUIN system deserve to be emphasised. One is the fine level of spatial disaggregation, particularly on the demand-side, where households are located across over 1500 spatial units. A second notable feature of RUIN is its emphasis on individual activity patterns. Ultimately, this permits a focus on spatial structure from the perspective of the supply-side, aswell as the demand-side which is more frequently considered, and we attempt to bring this out in subsequent sections. Finally, if the reader will pause to consider the requirements for modelling interaction flows from 1565 origin zones to 52 shopping centres, disaggregated by, say, seven ethnic groups, fifteen age groups and a further seven SEGs, then the advantages of the micro-level approach over the occupancy matrix representation should once again be apparent.

Table 3.1 Household and Individual attributes within the RUIN database.

HOUSEHOLD	INDIVIDUAL
1. Location	1. Status within household
2. Household structure and composition	2. Age
3. Tenure	3. Sex
4. Country of birth	4. Marital status
5. Primary retail location	5. Economic activity
	6. Socio-economic group
	7. Industry

4. MODELLING JOURNEY-TO-WORK FLOWS

It has been argued elsewhere (eg Wilson, 1986; Birkin and G.Clarke, 1987) that a crucial array for measuring labour market performance is $\{Y_{ij}(bags)\}$, where i and j are residence and workplace labels respectively, b is an occupation type or SEG, a is an age group, g an industry type, and s is the sex of a worker. We pick up the analysis of this array in Section 5.

As we have seen in Section 3, it is possible to input directly the array $\{X_i(bags)\}$ from the RUIN data-base. At the supply end, employment data is available in Britain for the arrays $\{Z_j(bg)\}$ and $\{Z_j(gs)\}$, at levels of resolution down to the individual ward. Interaction data between wards is in principle available, disaggregated by mode and sex ie $\{Y_{ij}(ms)\}$, although the 1981 data is still not generally available to the academic community. We were fortunate in having direct access to this data via a local planning authority.

The next step, and a rather important one, is how we conceptualise the model system which underpins the labour market, although to some extent this is a question of emphasis. In earlier applications of the performance indicator framework it has been assumed that although the employment distribution is a known quantity, it is something that functions as an attractor in the jobs market, rather than as a constraint as such (eg M.Clarke and Wilson, 1987). This produces a production-constrained model with obvious similarities to the shopping model. It is equally plausible, however, to consider an exact reversal of this state of affairs, such that it is the employment totals which are constrained, and residential locations are now a free summation. Obviously the housing market applications such as the Urban Institute model (de Leeuw and Struyk, 1975) and HUDS (Kain and Apgar, 1985) are of this type.

In this paper, however, we wish to pursue the principle of information retention which underpins the existing RUIN database, while recognising that in part this may only be possible because of the static nature of this approach, in contrast to the more markedly dynamic models referred to above (and see also Section 6 below). In mathematical programming terms, we have the following problem (in view of the available data discussed above):

$$\min_{\{Y_{ij}^{bags}\}} \sum_{bag} Y_{ij}^{bags} - \sum_{m} \hat{Y}_{ij}^{ms} \qquad (1)$$

s.t.

$$\sum_{j} Y_{ij}^{bags} = X_{i}^{-bags} \qquad (2)$$

$$\sum_{iag} Y_{ij}^{bags} = \bar{Z}_{j}^{bs} \tag{3}$$

$$\sum_{iba} Y_{ij}^{bags} = \bar{Z}_{i}^{gs} \tag{4}$$

In view of the constraints (2)-(4), the problem assumes the aspect of biproportional matrix filling. Earlier applications within RUIN have adopted a technique known as Iterative Proportional Fitting (IPF) to broach problems such as these (see Birkin and M.Clarke, 1987; Birkin, 1987). In this case, however, the more familiar techniques of spatial interaction modelling are available to us. The exact model structure depends on a variety of specific decisions which can be taken on the way in which constraints are compounded, and how modal split is treated. For present purposes we have elected to calibrate the following model:

$$\min_{\{\beta_{i}^{ms}\}} \sum_{jbg} Y_{ij}^{bgms} c_{ij} - \sum_{js} \hat{Y}_{ij}^{ms} c_{ij} \tag{5}$$

s.t.

$$Y_{ij}^{bgms} = A_{i}^{bgms} B_{j}^{bgs} \bar{\bar{X}}_{i}^{bgms} \bar{\bar{Z}}_{j}^{bgs} f(c_{ij}) \tag{6}$$

$$A_{i}^{bgms} = \left[\sum_{j} B_{j}^{bgs} \bar{\bar{Z}}_{j}^{bgs} f(c_{ij}) \right]^{-1} \tag{7}$$

$$B_{j}^{bgs} = \left[\sum_{im} A_{i}^{bgms} \bar{\bar{X}}_{i}^{bgms} f(c_{ij}) \right]^{-1} \tag{8}$$

where

$$\bar{\bar{X}}_{i}^{bgms} = \bar{X}_{i}^{bm} * \bar{X}_{i}^{bgs} / \bar{X}_{i}^{*m} \tag{9}$$

$$\bar{\bar{Z}}_{j}^{bgs} = \bar{Z}_{j}^{bs} * \bar{Z}_{j}^{gs} / \bar{Z}_{j}^{*s} \tag{10}$$

The calibrated data values for this model are shown in Table 4.1.

Once the array {Yij(bgms)} has been established, it is a fairly straightforward matter to generate and sample from cumulative probability distributions that will assign individuals to a zone of workplace. This relationship may be written as:

$$p\ (j,m \mid i,b,g,s) = Y_{ij}^{bgms} \ / \ \sum_{ibgs} Y_{ij}^{bgms} \qquad (11)$$

Finally, we must, of course, concern ourselves with the reliability of the simulated distribution at which we have now arrived. The aggregate correspondence between zonal employment totals is demonstrated in Table 4.2. Although the relationship is clearly an imperfect one, it is important to emphasise that at this stage the microdata base is itself the product of a modelling procedure. Thus the framework implied by equations (5)-(10) is not a direct representation of labour market processes, and assumes that we can allocate individuals to workplaces on the basis of their socio-economic group, industry type, sex and residence location (only). Furthermore, there are obvious imperfections within the modelling procedure itself. For example, we use an euclidean distance matrix with crude assumptions about intrazonal trip costs, while the whole of the spatial analysis is rather more coarse than we might like. In addition, the closure of the system leaves something to be desired at this point, as we observed in Section 3. Lastly, the Monte Carlo sampling procedure by which individuals are assigned attributes on the basis of some inferred probability distribution is itself subject to sampling errors, and these errors will inevitably be compounded as the attribute coverage is expanded (cf Birkin and M.Clarke, 1987).

On the positive side, the emphasis within the synthetic data generation exercise is ultimately on getting the interdependencies between attributes right. Thus it is likely that if the aggregate distributions are reliable, then this will be reflected at the micro-level. Notwithstanding the caveats discussed above, we believe that Table 4.2 does at least imply a data base in which we can have some confidence, and which provides a more than adequate input for the detailed analysis which now follows.

5.MODEL-BASED PERFORMANCE INDICATORS OF THE LOCAL ECONOMY

The main output from the simulation exercises of the previous two sections is the crucial array {Yij(bas}). The argument of this section is that this array offers far more detail on the operations and interdependencies of the local labour market than can be gleaned from secondary sources. An effective medium for analysing the array is through a suite of performance indicators - both residence-based and workplace-based (c.f Wilson 1986, G.Clarke and Wilson 1987). For illustrative purposes we look at just three residence and three workplace indicators. (A fuller list of indicators for the local labour market appears in the Appendix). The significance of each indicator will be explored in relation to a number of key selected wards. These will usually be the three wards introduced in section 2, North, Harehills and Richmond Hill, supplemented for the workplace indicators by other areas which contain more jobs.

5.1 Residence-based indicators

The main emphasis throughout this section is on different person types, disaggregated by social class, age and sex. We believe this type of analysis makes an important contribution to the 'personal characteristics' literature, which has already made inroads into how (un)employment (and deprivation more generally) varies with attributes such as age, sex, social class, tenure, race, qualifications etc. (Gordon 1986-table 4; van Dijk and Folmer 1985; Hasluck 1987; Worrall 1986). Although we do not include such a full range of attributes at this stage, they are an integral feature of the RUIN system and the more detailed interdependencies will be teased out at a later stage.

5.1.1 Employment and Unemployment Rates

The first indicators simply present more disaggregated basic accounting totals: the probabilities of residents in particular areas being employed or unemployed respectively.

Table 5.1 Employment and Unemployment Rates

	PROFESSIONAL AND MANAGERS			SEMI-SKILLED AND UNSKILLED	
NORTH	Male	Female		Male	Female
16-24	0.961	0.936		0.822	0.904
25-44	0.974	0.988		0.898	0.962
45+	0.972	0.987	(employment rates)	0.896	0.959
RICH/HILL					
16-24	0.891	1.00		0.559	0.972
25-44	0.886	1.00		0.647	0.987
45+	0.928	1.00		0.759	0.982
HAREHILLS					
16-24	0.960	0.885		0.593	0.885
25-44	0.978	0.96		0.675	0.971
45+	0.982	0.942		0.586	0.968
NORTH					
16-24	3.90	6.40		17.80	9.60
25-44	2.60	1.20		10.20	3.80
45+	2.80	1.30	(unemployment rates as percentages)	10.40	4.10
RICH/HILL					
16-24	10.90	0.00		44.10	2.80
25-44	11.40	0.00		35.30	1.30
45+	7.20	0.00		24.10	1.80
HAREHILLS					
16-24	4.00	11.50		40.70	11.50
25-44	2.30	4.00		32.50	2.90
45+	1.80	5.80		41.40	3.20

Table 5.1 shows the very high rates of unemployment and low rates of employment probabilities for the manual workers, especially in the younger age groups, in both Harehills and Richmond Hill. North, however, in the more affluent leafy suburbs, tends to have much higher employment probabilities and lower rates of unemployment, for all social classes. These kinds of figures support earlier research on activity patterns such as Webber (1978) who discovered a similar probability of the 'best' areas having much lower levels of unemployment than other areas, even for the unskilled categories. In a full RUIN simulation, which includes all the attributes of the population mentioned in the introduction to this section, it should be possible to shed light on whether the characteristics of the unskilled in these 'best' areas are any different from those unskilled in the 'worst' areas (the issue of 'deprived places' or 'deprived people'; c.f. Cullingford and Openshaw (1979)).

Also striking form Table 5.1 is the very much lower rates of unemployment for female workers, except for the professional group (n.b zeros in Richmond Hill indicate non present rather than nil unemployment). These types of result emphasise the benefits of the simulation approach, combining information on age, sex, occupation and location. Whilst there are numerous studies on the spatial or occupational variations in (fe)male unemployment for example, there are few which can effectively combine all the major personal attributes.

5.1.2 Average Distance Travelled

The indicator here is written formally as

$$C_i^{bas} = \sum_j Y_{ij}^{bas} d_{ij} \Big/ \sum_j Y_{ij}^{bas} \qquad (12)$$

and is the first to explicity incorporate the interaction matrix {Yij}: d_{ij} is the distance between i and j

Table 5.2 Average Distance Travelled (km)

	PROFESSIONAL AND MANAGERS		SEMI-SKILLED AND UNSKILLED	
NORTH	Male	Female	Male	Female
16-24	7.23	8.20	7.87	3.67
25-44	7.45	9.21	5.54	3.85
45+	8.52	3.90	5.63	5.18
RICH/HILL				
16-24	3.87	2.78	4.82	4.13
25-44	2.60	4.68	5.12	4.45
45+	3.97	3.90	4.14	3.75
HAREHILLS				
16-24	3.75	1.50	4.14	2.75
25-44	2.82	3.05	3.80	3.50
45+	2.60	2.30	3.86	3.85

The obvious feature of Table 5.2 is the much longer average distance travelled from all residents in North. This, of course, may not indicate a problem where the professional group is concerned since journey time may simply have been traded for housing and environmental quality. The high figures for the unskilled groups are perhaps more of a concern, not only in North, but also in Harehills and Richmond Hill. Both these wards have longer average travel distances to work for unskilled groups than professional groups, who seem to work in the locality itself or in the city centre nearby. (We can shed more light on this area by looking at number of residents finding jobs in their own localities- the degree of self-containment- in the next section).

It is interesting that rates of female travel in the local labour market are roughly in the same proportion as male rates, with the exception of professionals in North. This is generally because there are fewer jobs for professional women outside the central areas and hints at the levels of female penetration in managerial posts in more industrial areas. (see also the workplace indicators).

5.1.3 Degree of self-containment

The indicator to be explored here takes the following form

$$X_i^{bas} = Y_{ii}^{bas} / E_i^{bas} \qquad (13)$$

and clearly measures the degree to which residents can find jobs in their own locality.

Table 5.3 Degree of self-containment (residents)

	PROFESSIONAL AND MANAGERS		SEMI-SKILLED AND UNSKILLED	
NORTH	Male	Female	Male	Female
16-24	0.175	0.182	0.429	0.745
25-44	0.115	0.105	0.488	0.696
45+	0.117	0.278	0.410	0.619
RICH/HILL				
16-24	0.154	0.40	0.213	0.152
25-44	0.684	0.182	0.194	0.216
45+	0.158	0.111	0.305	0.243
HAREHILLS				
16-24	0.33	0.80	0.04	0.15
25-44	0.40	0.308	0.137	0.147
45+	0.38	0.60	0.085	0.171

As one might expect given the different amounts of jobs in each ward, there is quite a wide variation between social groups, age-groups and locations. In North, there are few male or female professional and managerial jobs and most of this group are forced to commute (remember the long journey times of the previous indicator). The degree of self-containment in Harehills is very much higher, although there are very many fewer professional workers demanding jobs from Harehills. The same is true for Richmond Hill although in this case there also seems to be a greater degree of out-commuting. The anomaly here is the 25-44 age group for male workers. It is difficult to conclude at this stage whether this is simply a small numbers problem or a reflection of the larger number of middle-aged managerial posts associated with local manufacturing industry.

On the unskilled side the figures are generally higher showing that some jobs are available locally to these areas. (Although bear in mind that the average distance travelled for these groups was quite high, suggesting relatively long-distance commuting for those who cannot find jobs locally). Harehills is the exception here offering very little in the way of local employment for the low-skilled and unskilled.

5.2 Workplace Indicators

For the analysis of workplaces we add a further set of attributes and consider persons of social group (b), age group (a), sex (s) and jobs of industrial type (g). However, only a basic 6-fold categorisation is used here: agriculture, energy and water, manufacturing, distributive trades, transport and services. Figs 5.1-5.2 show the spatial distribution of male employment for manufacturing and services. The figures refer to employment in those respective categories in each ward as a percentage of the total employment in that category. Alternatively, Fig 5.3-5.4 show female employment for manufacturing and services in each ward as a percentage of total employment within that ward.

5.2.1 Degree of market share

This indicator measures the number of jobs (in industry type g) provided in a particular workplace zone as a percentage of the total number of jobs across the whole market. Formally it is written as

$$X_j^{bags} = E_j^{bags} / \sum_i E_i^{bags} \qquad (14)$$

To explore this indicator we concentrate on those areas that have the highest overall employment totals.

Table 5.4 Degree of market share

a) City and Holbeck

	PROFESSIONAL & MANAG.		JUNIOR NON-MAN.		UNSKILLED	
	Male	Female	Male	Female	Male	Fem.
16-24	0.389	0.436	0.447	0.42	0.397	0.399
25-44	0.391	0.586	0.416	0.474	0.444	0.305
45+	0.400	0.509	0.424	0.376	0.384	0.356

b) Manufacturing (Male)

City & Holb.	SKILLED MANUAL	SEMI-SKILLED MAN.	UNSKILLED
16-24	0.151	0.192	0.185
25-44	0.157	0.173	0.227
45+	0.187	0.171	0.207
Hunslet			
16-24	0.139	0.153	0.171
25-44	0.113	0.152	0.170
45+	0.119	0.148	0.138
Rich/Hill			
16-24	0.057	0.03	0.085
25-44	0.06	0.035	0.068
45+	0.05	0.04	0.03

It is evident from Table 5.4 (a) that the central area of the city (including the city centre itself and the industrial area of Holbeck) still dominates the local labour market, providing over a third of all male professional jobs, half the total female professional jobs, a third to a half of all male and female clerical non-manual jobs and a third of all the male and female unskilled manual jobs. If we disaggregate to male manufacturing employment (Table 5.4 (b)) we can see the high rates of low-skilled employment concentrated in the south of the city. (Although we have argued Richmond Hill is a fairly large employment zone it nevertheless accounts for less than 10% of jobs for any social class/age category).

5.2.2 Size of market area

In order to determine the geographical extent of the market area for each ward we can calculate average distance travelled by persons working in that ward (the opposite to the residential 'average distance travelled' indicator). This is written as

$$XX_j^{bags} = \sum_i Y_{ij}^{bags} d_{ij} \Big/ \sum_i Y_{ij}^{bags} \qquad (15)$$

Table 5.5 Geographical size of market area (male)

i) CITY	Professional	Skill/man.	Sem/skilled	Unskilled
16-24	7.25	5.35	5.31	3.03
25-44	8.23	5.80	5.73	4.45
45+	8.99	5.83	4.49	4.40

ii) HUNSLET				
16-24	7.81	5.16	5.29	4.26
25-44	9.65	5.53	5.04	5.29
45+	7.34	5.67	5.07	4.49
iii) RICH/HILL				
16-24	5.24	4.28	5.50	5.81
25-44	9.19	5.09	5.33	4.62
45+	7.14	5.20	5.31	5.48

The obvious feature of Table 5.5 is the longer average distance travelled by professional workers coming into the workplace zones (compare with the distances travelled from the residential areas in Table 5.2), and the corresponding decline in distances travelled as one moves through the social classes. The generally high figures, compared with the residential totals, suggest a considerable amount of cross-boundary flows between areas and that even areas such as Hunslet and Richmond Hill attract professional and skilled workers from outer suburbs. We shall look in more detail at the interactions themselves in the next section.

5.2.3 Degree of self-containment

The third workplace indicator is simply the reverse of the last residence-based indicator. It measures the degree to which a particular workplace zone employs from residents within that zone (aggregated over all job types). Formally the indicator is expressed as

$$Y^{bags}_{j} = Y^{bags}_{jj} / E^{bags}_{j} \qquad (16)$$

For this indicator we return to our three previous study zones, North, Harehills and Richmond Hill.

Table 5.6 Degree of self-containment (workplaces)

	PROFESSIONAL AND MANAGERS		SEMI-SKILLED AND UNSKILLED	
NORTH	Male	Female	Male	Female
16-24	1.00	1.00	1.00	0.709
25-44	0.915	1.00	0.84	0.728
45+	0.875	1.00	0.862	0.904
RICH/HILL				
16-24	0.111	0.29	0.374	0.332
25-44	0.146	0.265	0.270	0.307
45+	0.069	0.250	0.482	0.263
HAREHILLS				
16-24	0.607	1.00	1.00	0.603
25-44	0.405	0.50	0.94	0.629
45+	0.687	0.75	1.00	0.70

We saw in the last section the openness of workplace areas that have a large number of jobs. In comparison we see that North and Harehills, which have comparatively fewer jobs at the extreme ends of the labour market, have a much greater degree of self-containment. The interesting ward again here however is Richmond Hill. Although it can obtain a third to a half of its unskilled labour force locally, it is very open to commuting from other areas of unskilled labour nearby; namely, Burmantofts, Seacroft, Hunslet and Halton (see map, Fig 2.2). This helps to account for the relatively large average commuting distances seen in the last section. The large concentration of unskilled labour in the south and east of the city is clearly a major feature of the local labour market.

We can get a clearer picture of the degree of interaction for unskilled workers across South and East Leeds by plotting the actual flows into Richmond Hill. Fig 5.5 illustrates the scale of commuting involved.

Similarily we can plot the flows of professional workers into Richmond Hill, which also showed both low rates of local penetration (Table 5.6) and long average journey to work lengths (Table 5.5). These are shown in Fig 5.6.

5.3 Summary

Out of a large and powerful array of data {Yij(bag }, we have selected a number of illustrative indicators and wards of the city to examine the degree of spatial interdependence in the local labour market. Although selective in approach, we have already begun to see the degree to which the local labour market is open to commuting and which type of residents (in which types of locality) are most disadvantaged in terms of job accessibility. Specifying a fuller range of attributes (tenure, race, educational attainment, job skills etc.) would clearly make the analysis even more powerful. This remains an important research task for the future.

There are however, a number of further issues we must address which will also increase the power and usefulness of the labour market information system. These form the subject matter of the next section.

6. DYNAMICS AND SPATIAL PLANNING

In this concluding section we wish to outline important research areas for the future and map out the research programme to come. We have argued that a combination of the micro-simulation procedure and more conventional spatial interaction modelling has enabled us to analyse important spatial interdependencies within our example of local labour markets. This has helped to take us beyond the more traditional indicators of simply zonal employment and unemployment. However, we are aware that the system so described is currently static. In reality, the relationships between people and workplaces is changing constantly and we need a framework flexible enough to incorporate both supply and demand- side dynamics. On the labour supply side, people enter and leave the labour force (voluntary or involuntary) and migrate between locations and occupations.

Vickerman (1984) suggests five types of change in residence-workplace relations; change of job only, change of residence only, change in either which ultimately leads to a change in the other (both voluntary of forced) and a simultaneous residence and job change. Similarily Gordon (1986) suggests there is considerable mobility of labour between both occupations and industries, although, as one might expect, much is relatively 'short distance' between neighbouring occupations or industries.

It is argued in detail elsewhere that the micro-simulation framework offers considerable potential in the modelling of household dynamics, by updating individual and household attributes using list processing (Birkin and M. Clarke 1987). This involves deriving conditional probabilities for events such as births, deaths, migrations (geographical and occupational), marriages etc., and invoking Monte Carlo sampling methods to determine whether eligible individuals undergo appropriate transitions. As far as labour markets are concerned we clearly need to combine previous work on population and migration dynamics (see M. Clarke 1984, 1986) with probabilities of occupational migration. Detailed studies of occupational mobilities, such as Blackburn and Mann (1979) for the 'working class' and Dex (1987) for women workers, should help in this direction.

In terms of the demand for labour we argued in the introduction that an important emphasis will remain on short-term forecasting in the guise of more traditional impact analysis. Changing the structure of employment in a particular locality (by adding to or reducing the number and type of jobs) is one obvious type of impact study which opens the way to analysing a variety of local economic initiatives. If we take up the challenge of section 2 and eventually supplement the ward-based information system with a firm-based one, then we can even begin to examine the likely impacts of major firm closures or restructuring policies (c.f Massey and Meegan 1982).

Finally there remains the important task of linking the labour market analysis to other areas of urban geography and planning. There are some obvious connections here. If we know the number of people in a locality, of social class (b), age (a) and sex (s), who work in industry type (g), then we can begin to make more formal estimates of individual and zonal incomes. This becomes a major advance on more traditional indicators of income such as car ownership rates. (c.f G.Clarke and Wilson 1987). Another important link with fiscal matters is the economic impacts of labour market changes, and we need to supplement the models of employment changes with multiplier models of local tax revenue and income changes (c.f Clarke and Keys 1980 and Nairn and Swales 1987).

The research agenda is clearly set!

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APPENDIX

Suite of performance indicators for local labour markets

(i) Residence-based

(a) Accounting sets

E_i^{bas} = employment in i

U_i^{bas} = unemployment in i

e_i^{bas} = employment rate in i

(b) Average distance travelled

$$C_i^{bas} = \sum_j Y_{ij}^{bas} d_{ij} \Big/ \sum_j Y_{ij}^{bas}$$

(c) Accessibility

$$A_i^{bas} = E_j^{bas} / d_{ij}$$

$$A_i^{bas} = E_j^{bas} / d_{ij}^{-\beta_i}$$

(d) Degree of self-containment

$$X_{i}^{bas} = Y_{ii}^{bas} / E_{i}^{bas}$$

(ii) Facility-based indicators

(a) Total number of jobs

$$E_{j}^{bags}$$

(b) Size of market area

$$XX_{j}^{bags} = \sum_{i} Y_{ij}^{bags} d_{ij} / \sum_{i} Y_{ij}^{bags}$$

$$XX_{j}^{bags} = \sum_{i} (Y_{ij}^{bags} / Y_{i*}^{bags}) E_{i}^{ba*s}$$

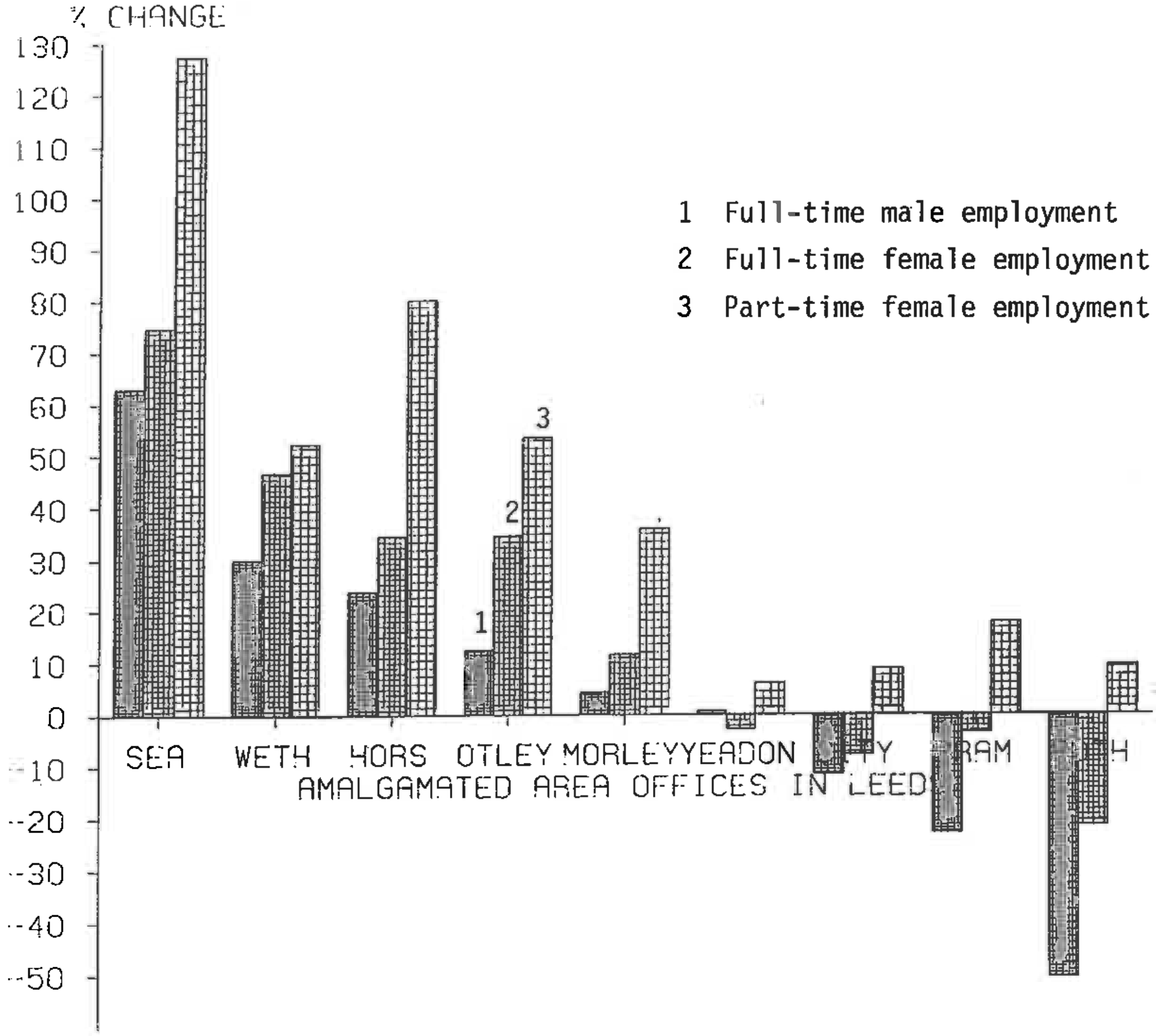
(c) Degree of self-containment

$$Y_{j}^{bags} = Y_{jj}^{bags} / E_{j}^{bags}$$

(d) Market share

$$X_{j}^{bags} = E_{j}^{bags} / \sum_{i} E_{i}^{ba*s}$$

Figure 2.1 Employment change in Leeds 1971-1981



Source: Census of Employment

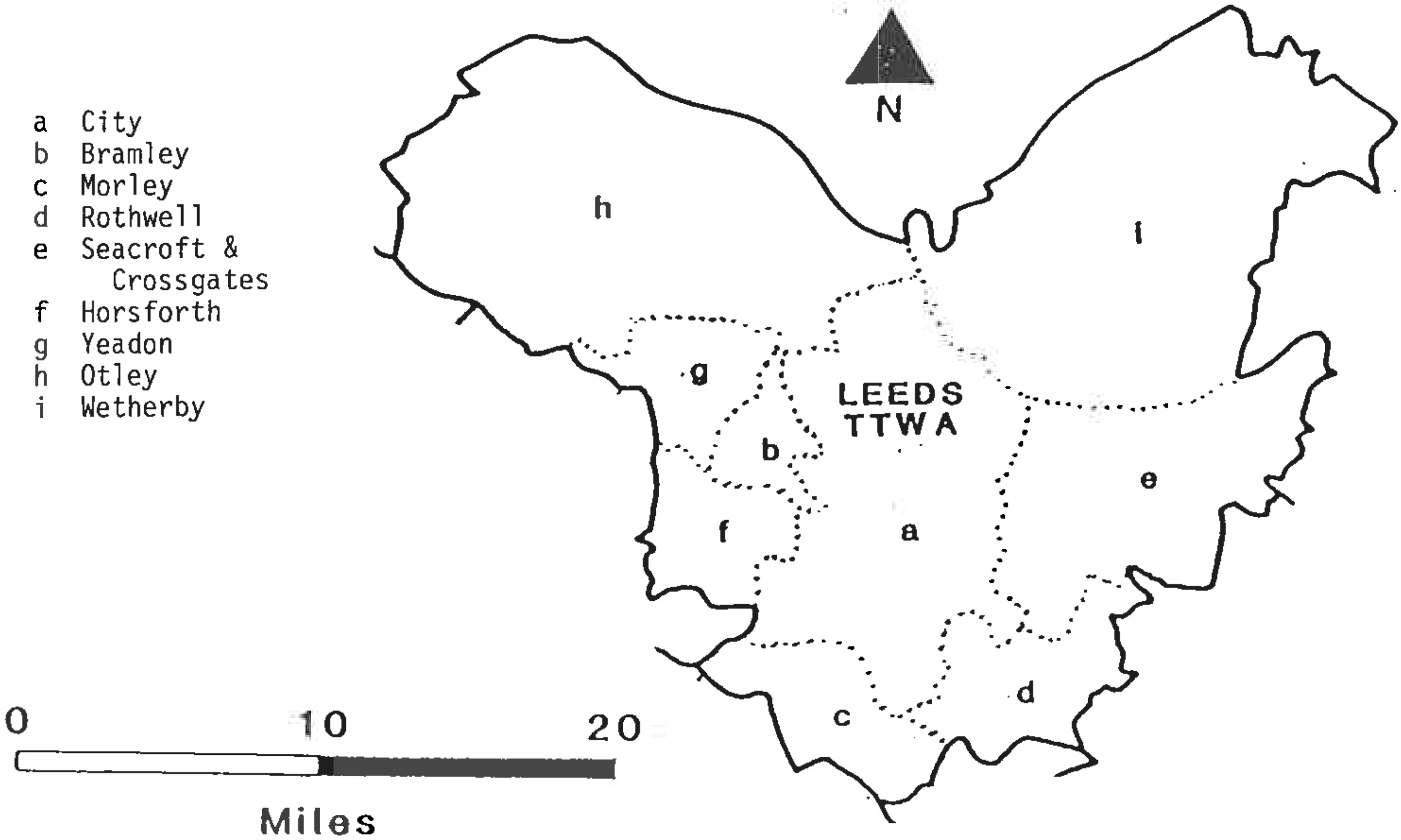
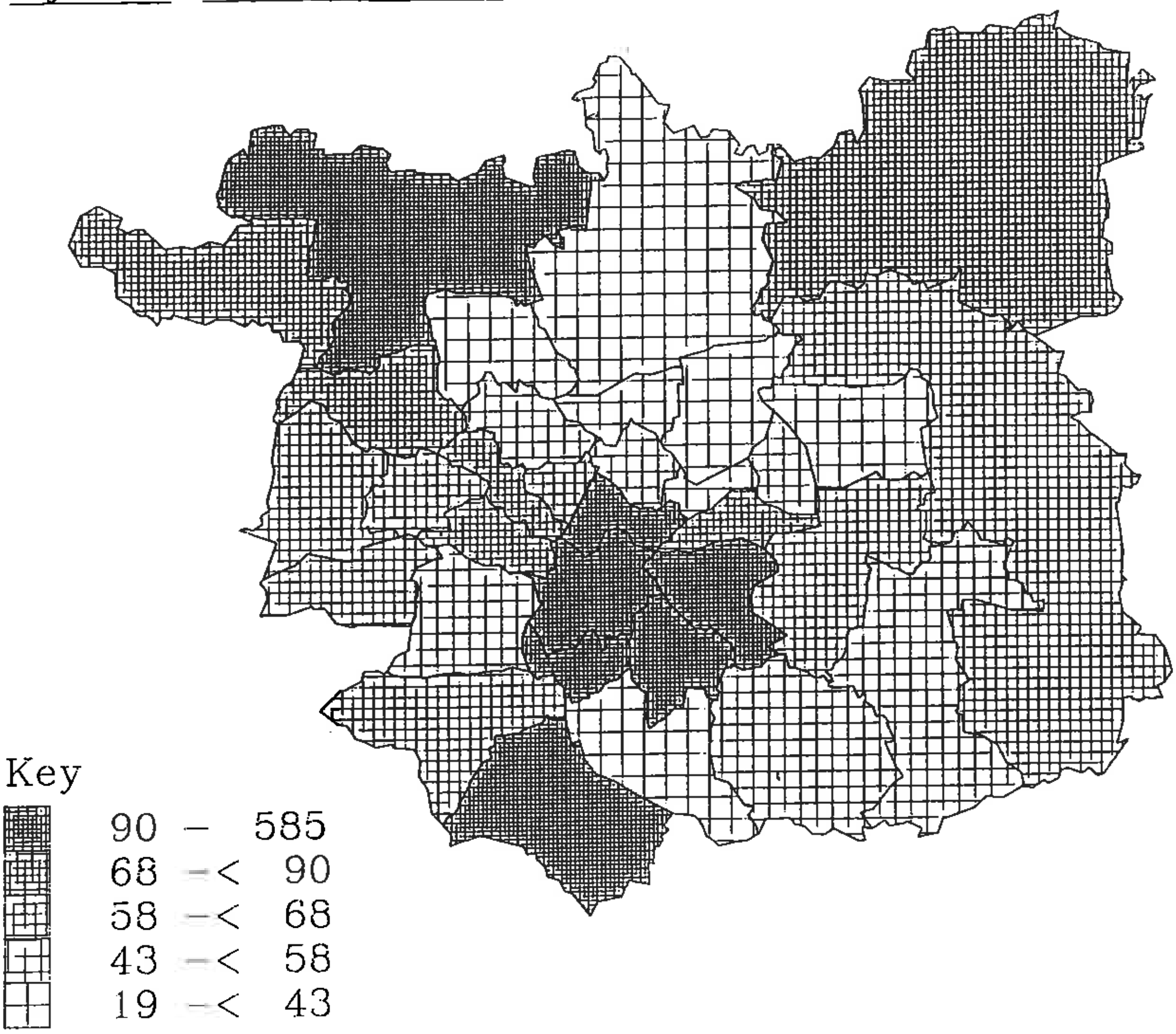


Figure 2.2 Number of jobs as a percentage of number of residents



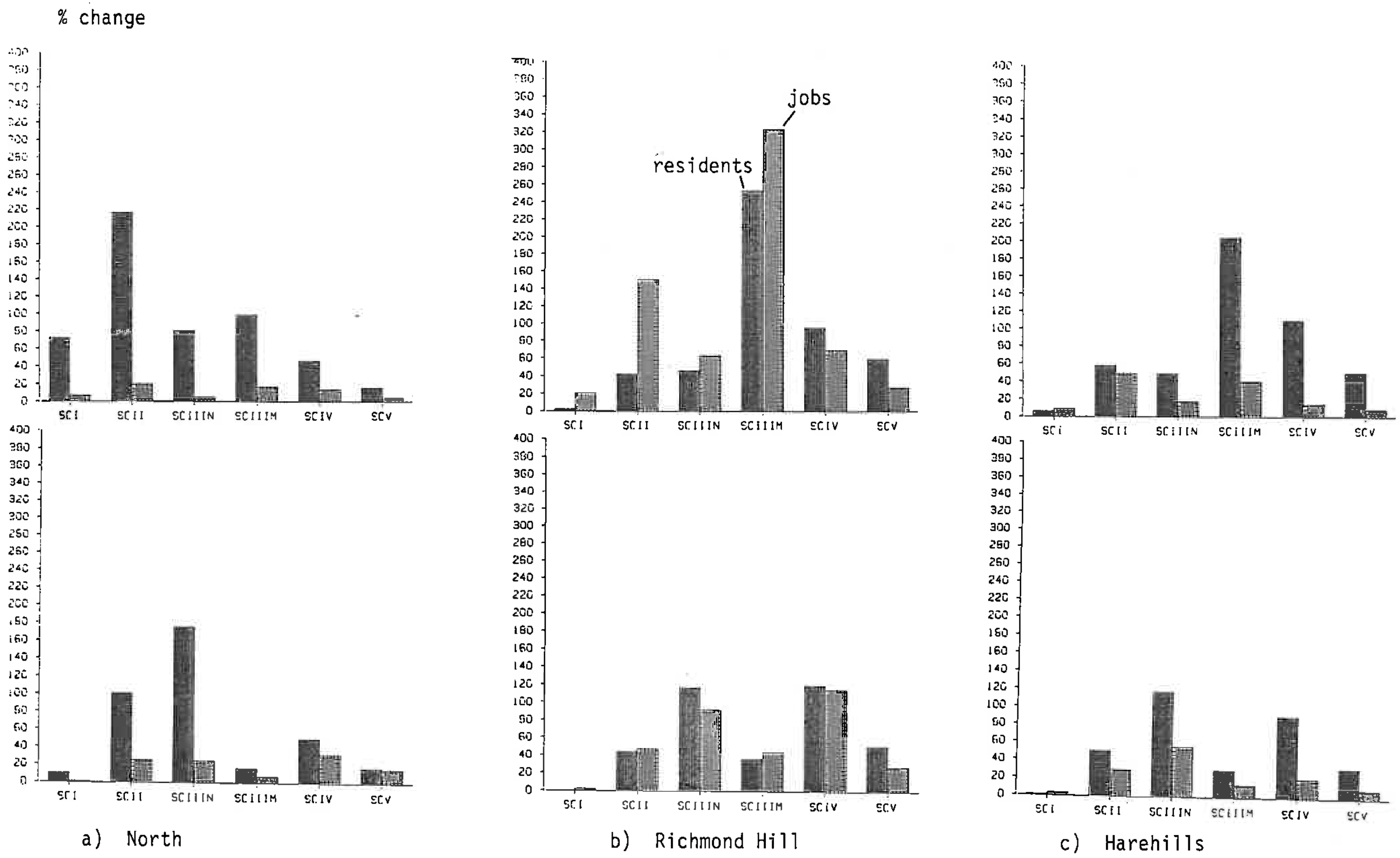


Figure 2.3 Employed residents and number of jobs by social groups

Job types - selected wards

Male

Female

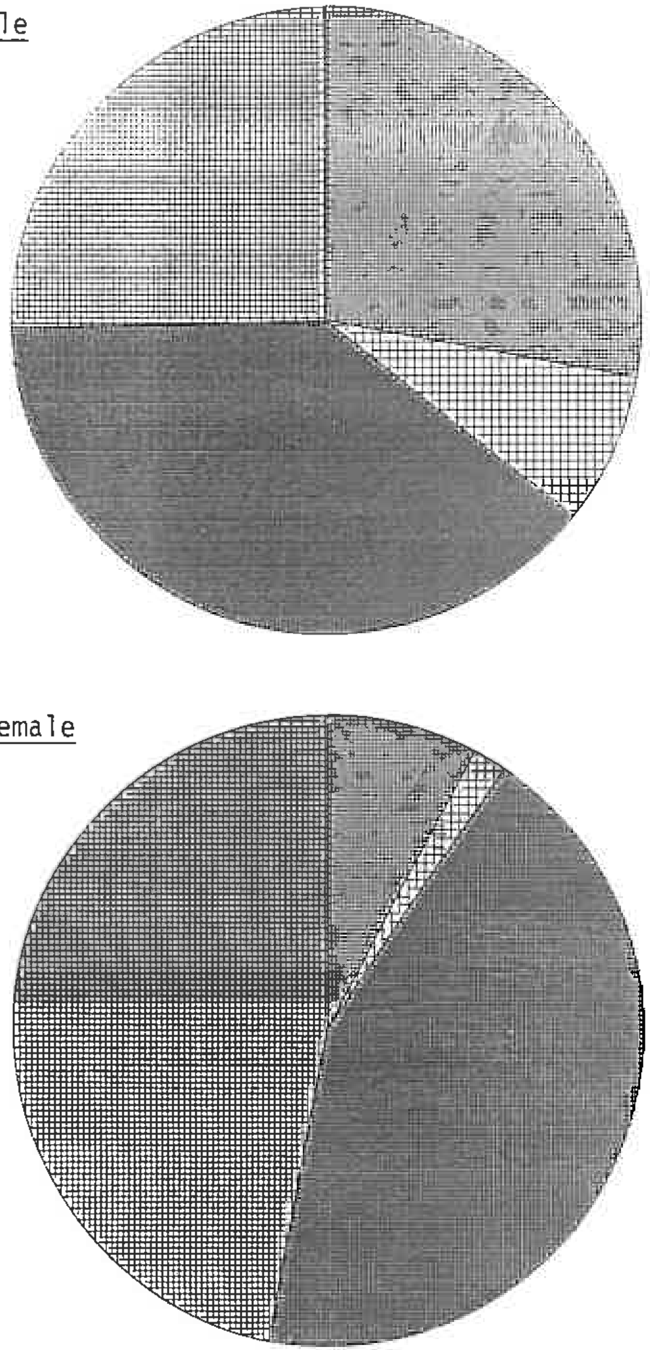


Figure 2.4 Harehills

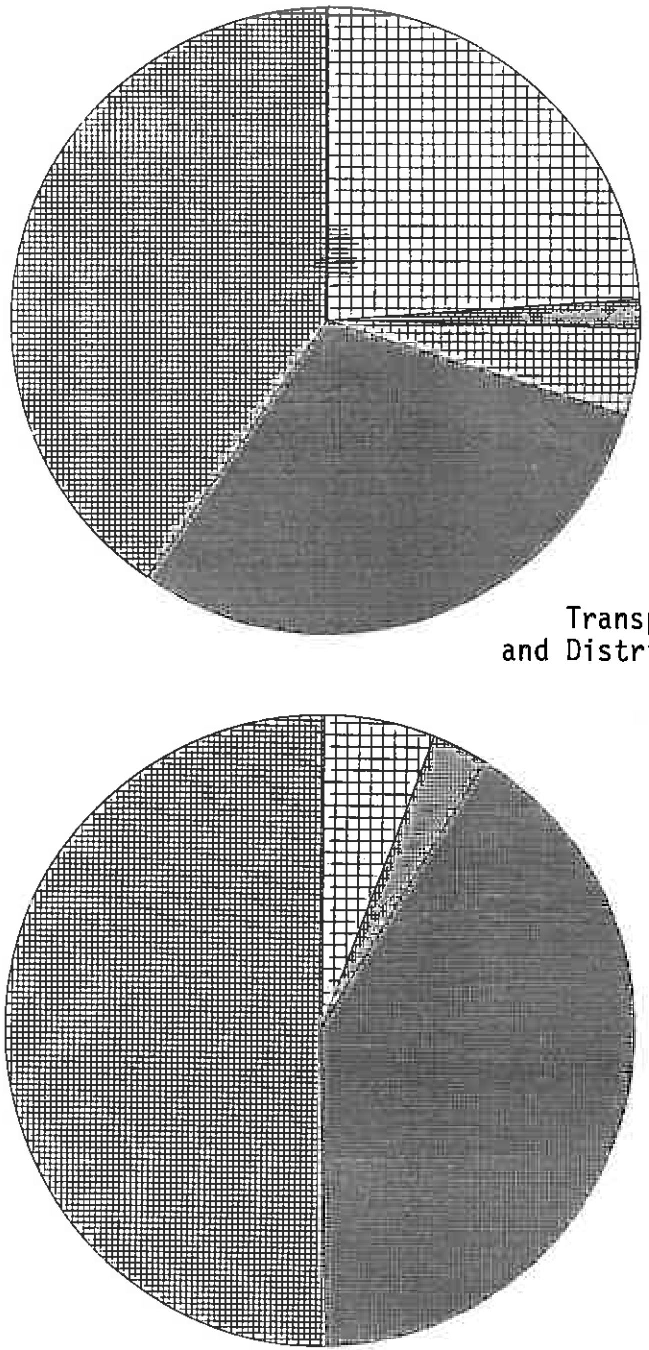


Figure 2.5 North

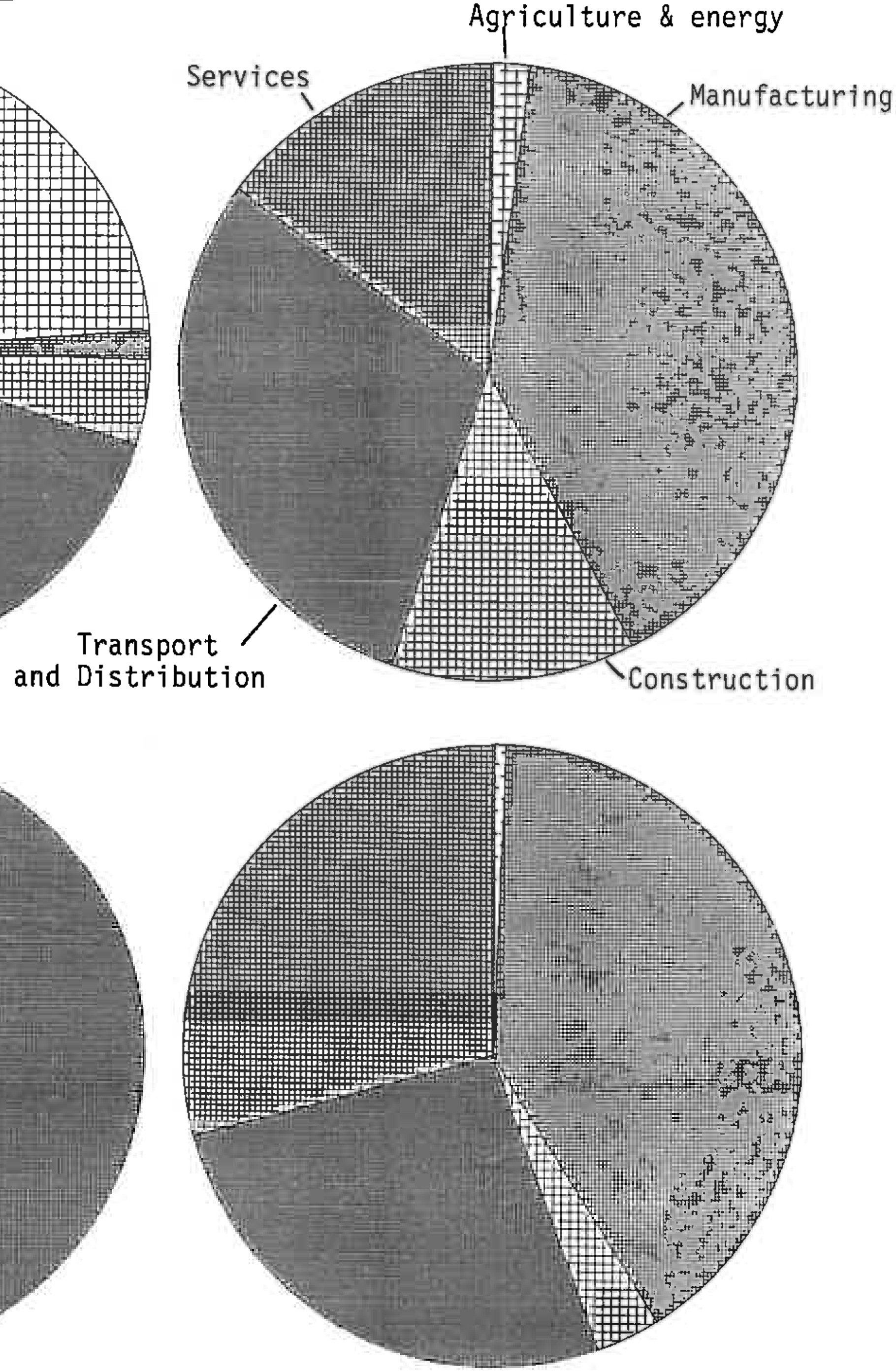
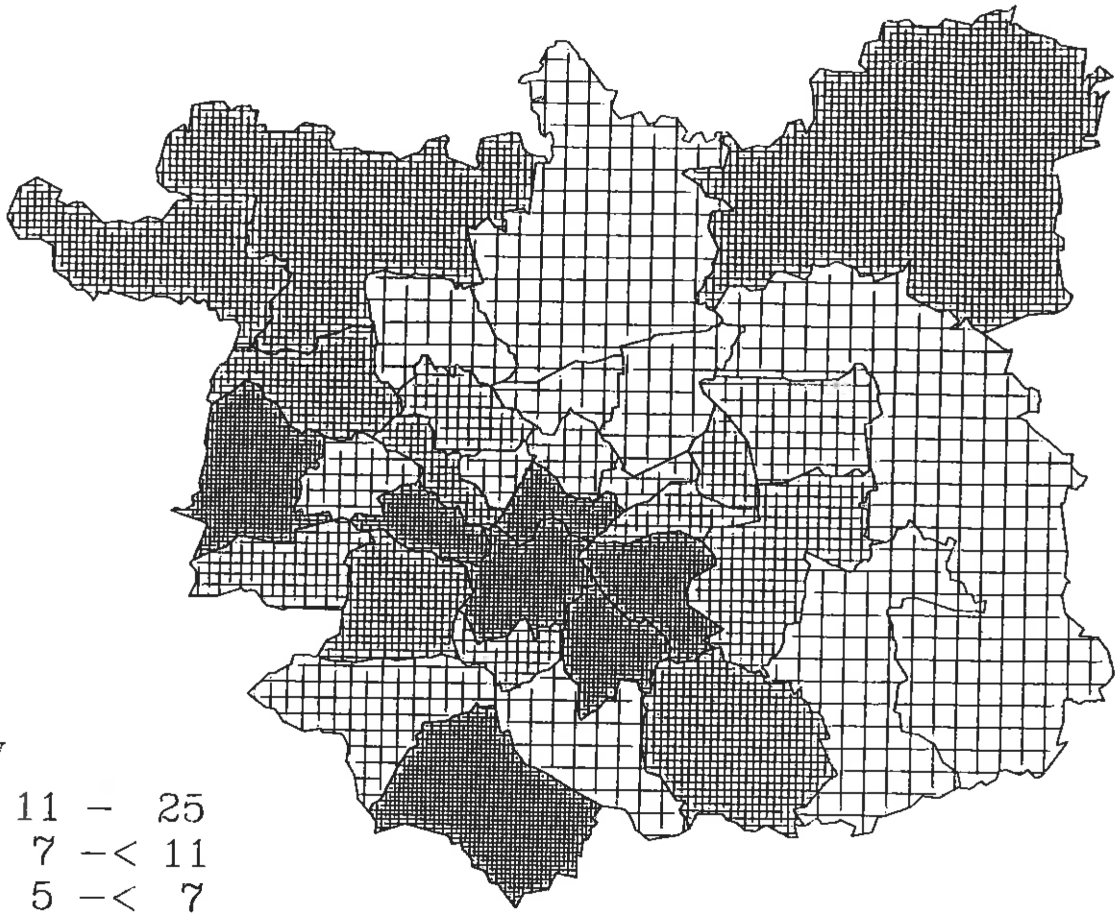


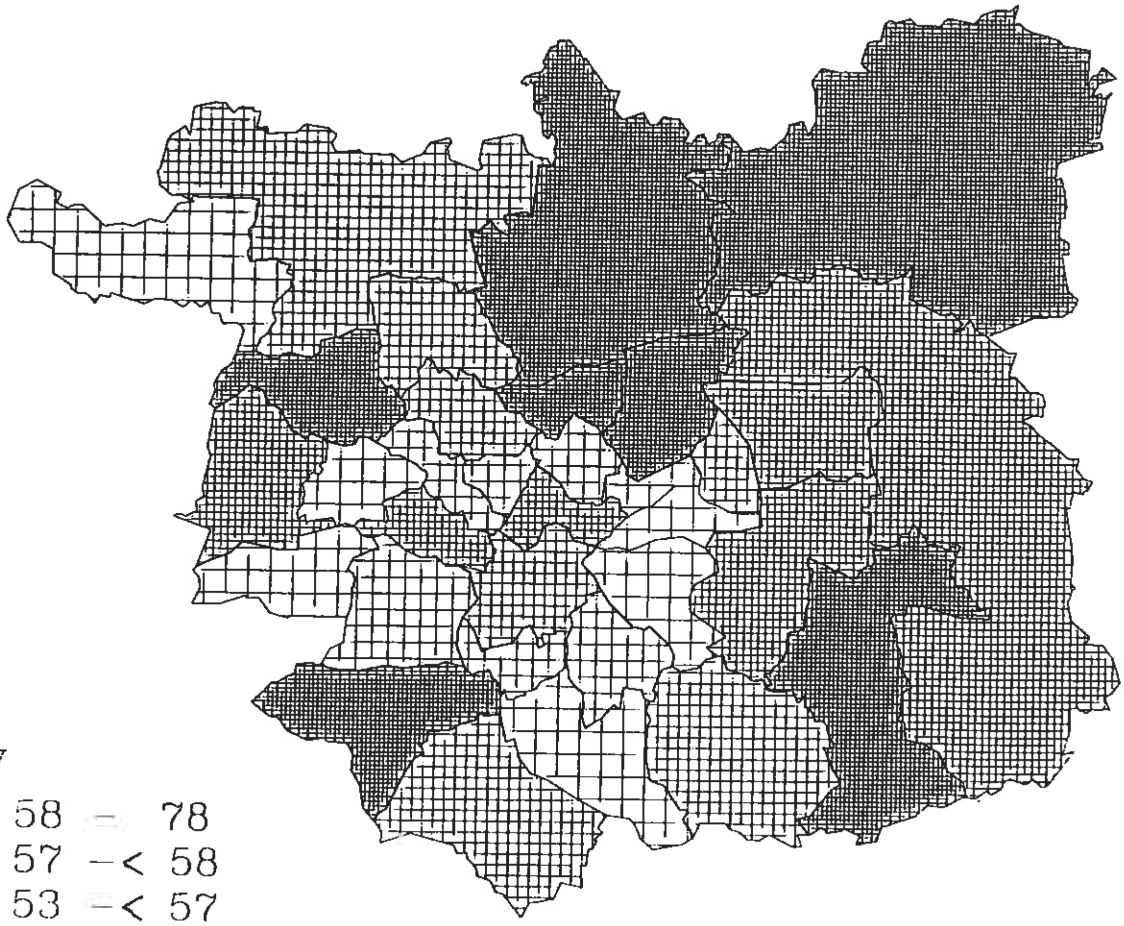
Figure 2.6 Richmond Hill



Key

11 - 25
7 -< 11
5 -< 7
3 -< 5
-0 -< 3

Figure 2.7 Number of firms employing >150



Key

58 - 78
57 -< 58
53 -< 57
49 -< 53
37 -< 49

(percentages)

Figure 2.8 Percentage of present-day firms that started business after 1970

Table 4.1 Calibrated beta values in the interaction model

Zone	Mode 1 M	Mode 1 F	Mode 2 M	Mode 2 F	Mode 3 M	Mode 3 F	Mode 4 M	Mode 4 F	Mode 5 M	Mode 5 F
1	1.6	1.0	1.5	1.0	0.6	0.2	5.7	2.0	2.1	1.1
2	0.8	0.8	1.1	1.1	0.1	0.1	2.7	2.4	0.4	0.4
3	1.2	3.6	4.8	5.9	0.9	2.0	10.0	10.0	9.3	10.0
4	0.6	0.7	0.6	0.8	0.2	0.3	2.1	2.8	1.2	1.7
5	1.4	1.4	1.6	1.6	1.6	1.6	4.4	3.8	2.1	1.9
6	1.7	1.4	2.0	1.6	0.2	0.1	4.5	2.8	2.1	1.6
7	1.5	0.7	1.9	1.0	0.1	0.1	4.3	2.8	1.7	0.9
8	0.3	0.2	0.4	0.4	0.1	0.1	1.0	0.9	0.4	0.4
9	2.3	1.1	2.5	1.2	1.9	0.9	10.0	3.0	2.0	1.0
10	1.4	1.9	2.3	2.0	1.6	1.4	9.8	7.4	4.4	5.9
11	1.4	1.3	1.7	1.6	1.4	1.5	4.7	3.2	2.6	1.9
12	2.3	1.4	3.0	2.0	0.1	0.1	6.5	3.4	2.5	1.7
13	1.0	0.8	1.5	1.2	0.2	0.2	5.5	3.7	1.2	1.0
14	1.3	1.1	1.3	0.9	0.7	0.5	3.6	3.0	1.7	1.3
15	0.5	0.8	0.6	1.0	5.0	5.0	1.5	2.3	1.1	1.6
16	0.9	1.0	1.2	1.5	0.2	0.2	4.0	2.8	0.8	1.1
17	1.8	2.4	2.4	2.9	0.1	0.1	4.5	6.0	2.2	2.7
18	2.4	1.2	3.2	1.5	2.9	1.5	10.0	4.3	2.3	1.2
19	1.0	1.9	1.1	2.1	0.3	0.5	3.1	3.3	1.9	2.6
20	0.6	0.9	0.7	1.0	0.1	0.3	2.5	2.7	1.0	1.4
21	8.7	4.1	10.0	4.9	5.0	5.0	10.0	10.0	10.0	5.3
22	1.2	0.8	1.3	0.9	0.6	0.2	6.9	2.6	4.1	1.3
23	1.2	1.9	1.4	2.1	0.8	1.3	4.8	3.0	2.2	2.3
24	1.6	1.5	1.6	1.4	1.0	0.9	8.1	4.3	2.2	2.0
25	0.7	0.9	1.0	1.3	5.0	5.0	2.5	2.8	1.3	1.6
26	1.6	2.1	1.9	1.9	0.6	0.6	4.5	3.1	3.5	2.9
27	3.0	2.2	4.0	2.8	0.3	0.2	10.0	8.6	4.1	2.8
28	2.4	1.7	2.7	1.9	0.6	0.3	4.0	2.7	3.7	1.9
29	0.6	0.3	0.8	0.5	0.1	0.1	2.4	1.9	0.8	0.6
30	1.7	1.4	2.1	1.7	0.2	0.2	3.5	3.9	2.0	1.6
31	0.9	0.7	1.2	1.0	5.0	5.0	4.1	2.4	3.1	2.0
32	3.3	2.5	3.7	3.0	1.6	1.6	10.0	5.3	8.8	4.1
33	1.1	1.5	1.2	1.7	0.2	0.3	3.0	4.1	1.8	2.6

Table 4.2 A comparison of observed and predicted employment totals

	Males Obs	Males Pred	Males Ratio	Females Obs	Females Pred	Females Ratio
1	497.	887.	17.8	390.	634.	16.3
2	459.	753.	16.4	310.	561.	18.1
3	424.	786.	18.5	133.	242.	18.2
4	537.	1009.	18.8	237.	393.	16.6
5	290.	515.	17.8	221.	357.	16.2
6	333.	608.	18.3	310.	529.	17.1
7	224.	390.	17.4	289.	482.	16.7
8	4894.	9120.	18.6	3688.	6880.	18.7
9	112.	216.	19.3	181.	309.	17.1
10	282.	502.	17.8	202.	338.	16.7
11	408.	729.	17.9	251.	461.	18.4
12	137.	239.	17.4	134.	208.	15.5
13	249.	411.	16.5	198.	324.	16.4
14	361.	584.	16.2	323.	566.	17.5
15	944.	1812.	19.2	307.	572.	18.7
16	424.	794.	18.7	179.	314.	17.5
17	120.	164.	13.7	91.	129.	14.2
18	110.	226.	20.5	179.	314.	17.5
19	420.	715.	17.0	209.	360.	17.2
20	605.	1056.	17.5	370.	663.	17.9
21	67.	180.	26.9	105.	202.	19.2
22	594.	1173.	19.7	376.	700.	18.6
23	545.	1025.	18.8	249.	448.	18.0
24	327.	561.	17.2	283.	501.	17.7
25	501.	1303.	26.0	371.	613.	16.5
26	275.	476.	17.3	207.	349.	16.9
27	133.	286.	21.5	133.	216.	16.2
28	199.	347.	17.6	192.	339.	17.7
29	1321.	2474.	18.7	1247.	2342.	18.8
30	244.	354.	14.5	197.	280.	14.2
31	492.	833.	16.9	380.	639.	16.8
32	151.	306.	20.3	110.	191.	17.4
33	375.	691.	18.4	194.	312.	16.1

Figure 5.1 Male employment in manufacturing (% of all manufacturing employment)

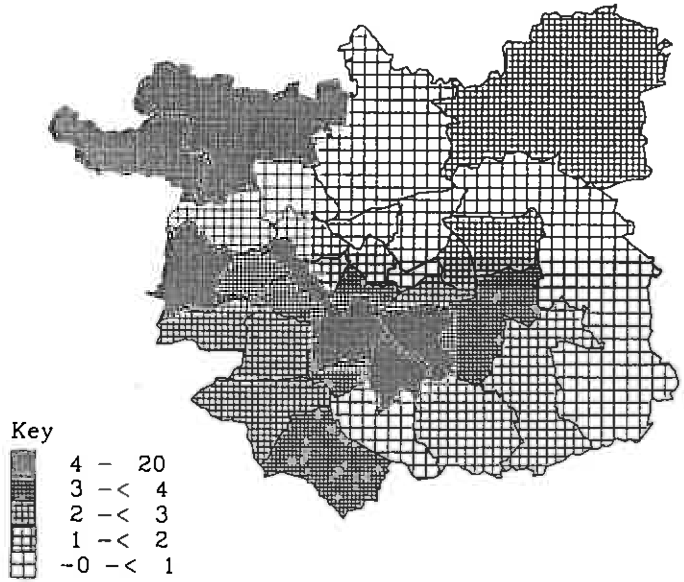


Figure 5.3 Female employment in manufacturing (% of ward employment)

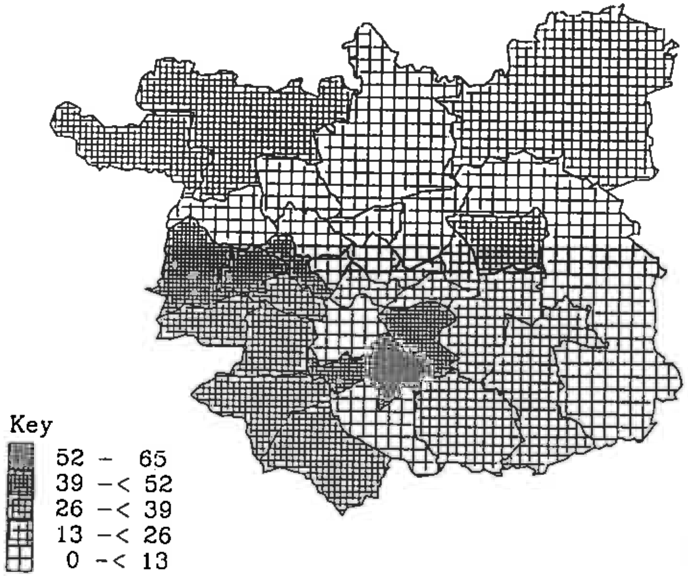
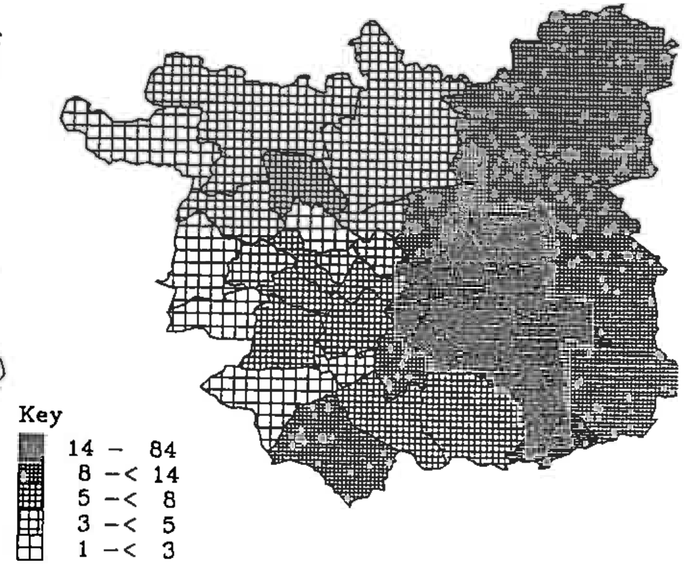


Figure 5.5 Work journeys to Richmond Hill (x) - semi-skilled and unskilled workers



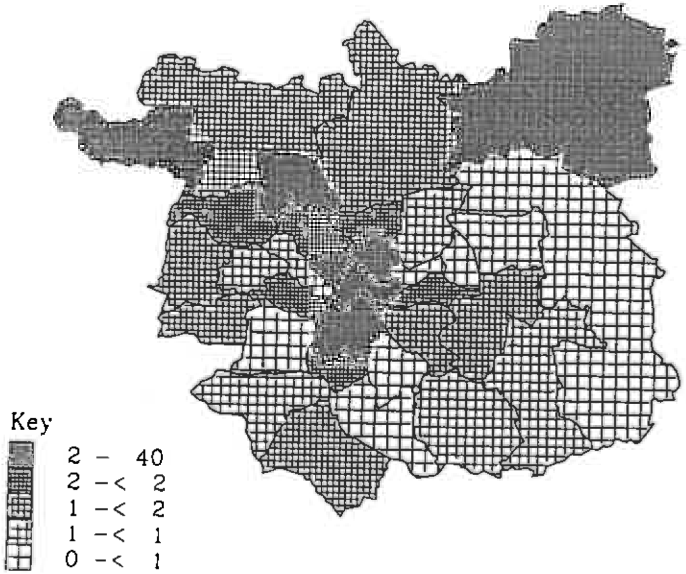


Figure 5.2 Male employment in services (% of all services employment)

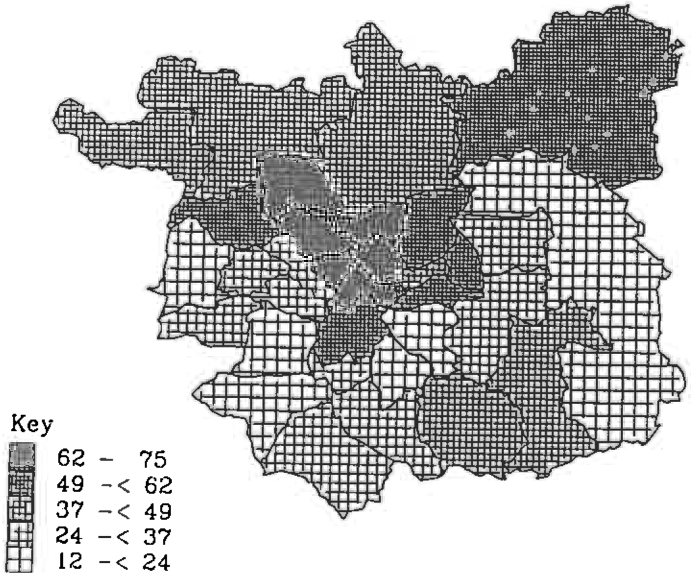


Figure 5.4 Female employment in services (% of ward employment)

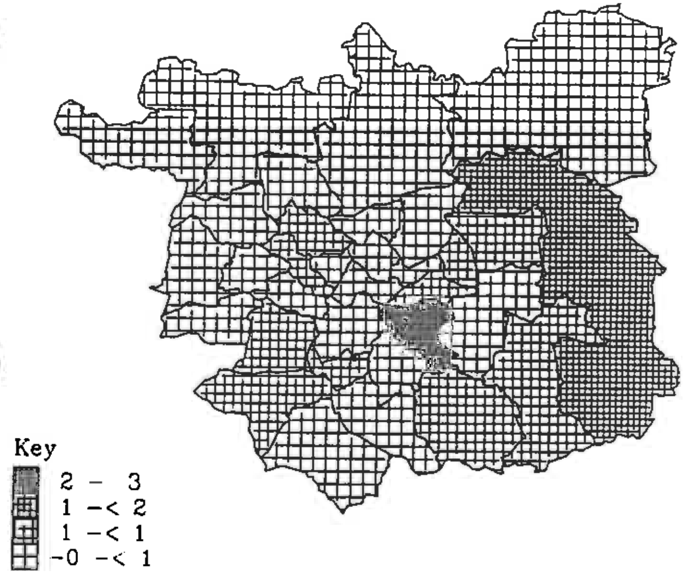


Figure 5.6 Work journeys to Richmond Hill (x) - professional workers