PLACE AND PERSONAL CIRCUMSTANCES IN A MULTILEVEL ACCOUNT OF WOMEN’S LONG-TERM ILLNESS

R. D. WIGGINS¹, H. JOSHI, M. BARTLEY², S. GLEAVE, K. LYNCH, and A. CULLIS

¹ Also of Department of Sociology, City University, London, U.K.
² Also of Department of Epidemiology and Public Health, University College, London, U.K.

Abstract

This paper investigates geographical variations in women’s reports of limiting long-term illness in terms of individual inequalities and the contribution of area characteristics among wards and county districts. We use multilevel modelling of linked census data from the Office for National Statistics Longitudinal Study for England and Wales. We follow a random sample of 76,374 women aged between 16 and 45 at the time of the 1971 Census for 20 years to observe their reported limiting long-term illness (LLTI) at the 1991 Census. Car and home ownership were useful markers of social and material advantage, apparently protecting against the risk of reporting LLTI. Migration into the South-East region appeared beneficial, but otherwise there was little difference between those who moved home and those who did not. Differences between county districts persist after adjustment for

* This paper has already been published in Social Science and Medicine, special issue, vol. 54, no. 5, March 2002, p. 827-838.
individual circumstances (education and ethnicity), but almost all of these differences are explained by the social profile of wards in these areas. Geographical differences in LLTI are not, therefore, entirely explained by the distribution of individual characteristics; a woman with the same history may face a different risk of illness in different kinds of area. For women, the social composition of the locality (using the ward as a proxy) is more relevant than the broader economic and industrial classification of the surrounding county district, which is more important for health inequalities among men.

**Keywords**: Women’s health, Geographical differences, Limiting long-term illness, Multilevel modelling, ONS Longitudinal Study.

**Résumé**

Les auteurs examinent les variations géographiques des déclarations de maladies invalidantes de longue durée (MILD) chez les femmes, en termes d’inégalités au niveau individuel et de caractéristiques locales au niveau des localités et des districts. Ils appliquent un modèle multi-niveaux aux données censitaires appariées de l’Étude longitudinale menée en Angleterre et au pays de Galles par l’Office for National Statistics. On a suivi pendant 20 ans un échantillon aléatoire de 76 374 femmes âgées de 16 à 45 ans au moment du recensement de 1971, afin d’observer leurs déclarations de MILD au recensement de 1991. Être propriétaire de son logement et posséder une voiture sont de bons indicateurs d’une situation sociale et matérielle confortable, qui semble protéger contre le risque de déclarer une MILD. Migrer vers le sud-est du pays paraît être un élément favorable, mais, à part cela, il n’y a peu de différence entre migrants et sédentaires. Les différences entre districts subsistent une fois que l’on a contrôle les caractéristiques individuelles (niveau d’instruction et origine ethnique), mais elles sont presque toutes expliquées par le profil social des localités dans ces diverses zones. Les différences géographiques de déclaration des MILD ne sont donc pas entièrement imputables à la répartition des caractéristiques individuelles ; à partir de la même histoire personnelle, une femme peut faire face à des risques de maladie différents dans des zones géographiques différentes. Pour les femmes, la configuration sociale de la localité est plus déterminante que les grandes caractéristiques économiques et industrielles du district qui l’environne, tandis que le district joue un rôle plus important dans l’explication des différences de santé chez les hommes.

**Mots-clés** : Santé des femmes, Différences spatiales, Maladie invalidante de longue durée, Modèles multi-niveaux, Étude longitudinale de l’ONS.
1. Introduction

Existing research on the social patterning of women’s health draws attention to the significance of social roles and socioeconomic position (Arber, 1997; Macintyre and Hunt, 1997). This paper approaches the less well explored question of geographical variations in women’s health. It asks what role may be played by geographical variations beyond differing social composition and economic structure. It draws on recent conceptual frameworks, which emphasise the role of area in understanding health inequalities (Arber, 2000; Curtis and Rees-Jones, 1998; Macintyre et al., 1993; Moss, this volume). We explore women’s health inequalities in England and Wales at two levels of geographical aggregation.

In the examination of area based inequalities in health, it is conventional to distinguish between ‘contextual’ and ‘compositional’ factors (Reijneveld and Schene, 1998). Area composition comprises those characteristics, which are the product of the aggregation of individual residents. A good example is the ‘deprivation score’, derived from the numbers of individuals in an area who are in a disadvantaged social class, unemployed, without cars, living in council accommodation and so on. Area context can be seen from several perspectives. In some work, context is conceptualised as an emergent property of the aggregation of individual characteristics. Although data on the individuals may guard against committing the ‘ecological fallacy’ (Robinson, 1950), Curtis and Rees-Jones (1998) warn against the risk of committing an ‘atomistic fallacy’ where the collectivity is more than the sum of its parts. ‘Non-deprived’ individuals have, for example, been found to have a higher risk of illness in areas where large numbers of ‘deprived’ persons live (Shouls et al., 1996). Sloggett and Joshi (1998b) report a similar finding for housewives but not employed women nor men.

Other studies regard context as more appropriately measured in the objective nature of the physical or economic environment. For example in terms of climate, the quality of local shops and transport, employment opportunities, the availability of open spaces, and other leisure facilities and services. There are also more subjective definitions of place, its scenery and security, as experienced by the inhabitants, and perceived in its reputation by others which may affect morale, the quality of life and health (Curtis and Rees-Jones, 1998; Gattrell et al., 2000). Curtis and Rees-Jones (1998) suggest a conceptual map to help understand the relationship between area and health experience by describing
a set of overlapping landscapes: ecological (e.g. industrial pollution); materialist (e.g. the quality of the housing stock); consumption (e.g. lack of public transport); and therapeutic (e.g. the degree of social cohesion). The classical policy questions which can be addressed within this conceptual framework are those concerned with the effects on quality of life and health in those with moderate or low income of improvements in the provision of public goods and services (Bartley et al., 1998; Lynch et al., 2000).

The literature on area differences in health has in fact highlighted a number of factors (Macintyre et al., 1993; Williams and Ecob, 1999) which might well be expected to affect women differently, and in some case more strongly, than men. The presence of adequate shops, services and transport and the security of the streets for example, might be more important for women. The nature of a ‘healthy’ local labour market, also, will be quite different for women. Large numbers of heavy, dirty and dangerous jobs such as mining create a trade off in health terms for men between income and health risk. A local economy with large numbers of clerical, sales and service jobs in contrast may leave a pool of ‘unemployable’ men at risk of all the accompanying health hazards while creating a situation in which women have greater employment prospects and thereby control over their living standards.

Our investigation focuses on the relationship between women’s ill health and their personal and local material circumstances. We apply multilevel modelling to the ONS Longitudinal Study (LS) to analyse self-reported limiting long-term illness. The LS is a 1% linked sample of individuals from the 1971, 1981 and 1991 Censuses (Hattersley and Creeser, 1995) for England and Wales. The question on limiting long-term illness, new in the 1991 Census, asks whether the respondent had a long-term illness, health problem or handicap which limits her daily activities or the work she can do. The responses are referred to hereafter as LLTI. Interestingly, Dale (1993) notes that pre-census test on the LLTI correlated well with other data on GP consultancies and inpatient and outpatient visits to hospital. She argues that it provides the only nationally consistent indication of health service needs.

In this analysis geography is represented by a population hierarchy where local neighbourhoods coincide with the boundaries of electoral wards and larger areas are described by county district boundaries. This describes a three level hierarchy whereby individual women are grouped in wards within county districts. The variation in LLTI is partitioned into three distinct components: individual variation between
women living in wards; that between wards within larger county districts and finally the variation between county districts themselves. The variation between individuals and both levels of area is modelled by including characteristics drawn from the census which portray social composition at both the individual and area level. Inequalities in health between women are a subject of interest in their own right, but in addition, we compare the results with those obtained for men.

The first step in investigating the relationships between individuals, area and health is to see if we can explain the area differences entirely on the basis of the characteristics of the resident women alone. Sloggett et al. (1993) using mortality as an outcome first attempted to answer this question using the LS. The analysis involved ordinary (single level) regression, which combined individual characteristics and aggregated information on the area of residence at the individual level. This was the only technique available at the time. A subsequent comparison of single and multilevel analyses of LLTI using data from three decennial censuses by Gleave et al. (1999) showed very similar estimates of regression coefficients under both approaches. Multilevel modelling was able to quantify the variation left unexplained by individual attributes and measured characteristics of the area.

2. Background

Geographical variation in the mortality of both men and women, both between and within regions is well known (Britton et al., 1990; Sloggett et al., 1993). A health disadvantage to living in northern regions, ‘the North-South divide’, has long been noted (Shaper, 1984; Sloggett and Joshi, 1994; Ecob and Jones, 1998). Despite sharp, yet uneven, decline in national mortality rates since the 1980s (Phillimore et al., 1994; Drever and Whitehead, 1997), Britain in the 1990s has the largest regional mortality differences in the postwar period (Shaw et al., 1999).

In 1991 for the first time, a British Census included a question on long-term illness, which limits the activities of the individual. The results have shown sharp regional differences in this measure, which largely parallel those for mortality but limiting long-term illness is more concentrated geographically than mortality (Langford and Bentham, 1996). By exploiting the spatial dimension in the LS we are in a posi-
tion to reveal how far those women in poor health according to self-reports of LLTI are clustered in areas of high social deprivation and begin to explain why this might be.

These regional differences could be due to women with different personal histories and characteristics living in different areas: ‘the compositional effect’. Alternatively, they could be due to a variety of ‘contextual effects’ as outlined above. What further insight does the literature provide about the relationship between health and deprivation?

There is a large literature on the identification and healthiness of ‘deprived areas’ (e.g. Britton et al., 1990; Carstairs, 1995; Charlton, 1996). ‘Deprivation’ has usually been defined as some combination of variables measured in the census such as unemployment, low social class and poor quality or public rented housing. These indicators are often regarded as representing poverty, though they are not perfect proxies for low income. Townsend (1991) describes adverse effects on living standards and health of London’s ‘deprived neighbourhoods’. This implies that health variations would not be explained by individual characteristics alone, and that broader influences on health would be reflected in community-level factors. Macintrye et al. (1993) list ways in which areas may be more or less healthy than would be expected given the composition of their residents: physical features of the local environment (e.g. pollution, traffic); conditions at home/work/play (e.g. parks and gardens); the quality and accessibility of health and other services; activities in the neighbourhood such as crime or political activism; and the place’s reputation. The latter may act to reinforce individual disadvantage. A further source of community health is the notion of social capital from ‘feeling part of the community’ (Mitchell et al., 2000). In this study civic engagement had a positive independent influence on health.

The interplay of local context, composition of the individuals living in the area and the individual’s own characteristics have been investigated in a variety of ways. Macintyre and colleagues (1993) conducted a qualitative study of contextual contrasts between two areas of Glasgow. Quantitative approaches range from ecological studies of standardized mortality related to census-based indicators of deprivation (e.g. Eames et al., 1993), including variables relating to neighbourhood socio-economic composition in a regression on individual characteristics (Sloggett and Joshi, 1994), and allowing interaction between individual and community-based variables (Blaxter, 1990). Multilevel
modelling had previously been used to examine effects of area and area classifications (e.g. Congdon, 1995; Duncan et al., 1993; Gould and Jones, 1996; Shouls et al., 1996).

This paper applies multilevel modelling to individual data in the LS, the largest scale English and Welsh data source which enables ward level data to be confronted with data on individuals. Results using single-level regression analysis suggest that much of the variation in several health indicators (e.g. death, long-term illness and low birthweight), which is systematically associated with the ‘deprivation’ of the locality at previous censuses, can be statistically accounted for by the characteristics of the individuals living in each area (Sloggett and Joshi, 1998a and b). This suggests that if there are any contextual effects on health, they are not well detected by a crude uni-dimensional indicator of deprivation, although such deprivation measures are conveniently based on census evidence. Using census indicators, Charlton (1996) finds that rural wards appear ‘healthy’ whatever the level of deprivation. The degree of urbanization and of affluence are also an independent component of the contextual elements found, alongside important individual components, in variations between districts by Shouls et al. (1996), using the Sample of Anonymised Records (SARs) from the 1991 Census as a data source (CMU, 1993; Marsh, 1993; Marsh and Teague, 1992). The individual component was less salient in the multilevel analysis, by Humphreys and Carr-Hill (1991), of the Health and Lifestyle Study, clustered in 396 wards.

In our parallel work, on men, we did a multilevel analysis on sample of 69,352 also aged between 16 and 45 in 1971 (Wiggins et al., 1998). This revealed that the wide variations between districts in LLTI in 1991 were only partly explained by men’s individual experience of unemployment, low social class and other disadvantages in 1971 and 1981. Further explanation was contributed by including the type of areas according to the ONS typology of districts (Wallace and Denham, 1996). We concluded that the experience of disadvantage over time affected the risk of reporting LLTI, but did not explain all of the geographical differences. Men with the same characteristics and work and migration histories report LLTI at different rates in different types of area. In this paper we ask ‘How does geography come into the explanation of social variations in LLTI for women?’

The analysis for women moves forward from our previous multilevel exercises, in two important ways. Firstly, we extend our geographical hierarchy to include ward, as a proxy for neighbourhood,
nested within county districts. Secondly, we typify the aggregate character of wards by using our own census-based scores. Districts are classified, using the ONS classification (Wallace and Denham, 1996), as in Wiggins et al. (1998). We are well aware that wards and county districts are imperfect descriptions of neighbourhood and space, and that census-based indicators have their limitations as either physical or psychological descriptions of the context.

To avoid substantial data loss we have abandoned any individual social classification or history based on occupational classification. These are especially unsatisfactory for women who do not always report an occupation, and for whom any occupation that is reported may not be a good indicator of her usual living standards. Those occupations, which are recorded for women, do not distinguish well between different levels of skill (Rees, 1992; Sacker et al., 2000). Furthermore, there are problems with identifying change of occupation over time, as classifications change (Blackwell, 1998). Instead, we follow the recommendation of Moser et al. (1988) and use access to a car and housing tenure over time as markers of individual circumstances. Arber (1991) suggests that such consumption measures may be equally or more revealing of a woman’s class position than occupation, perhaps because they are resources that make a difference in a woman’s everyday life. Macintyre et al. (1998) also suggest that they may not only be related to health because they are markers for income or psychological traits; they may also have some directly health promoting or damaging effects.

Our approach is, first, to clarify whether geographical variation is any greater than one would expect on the basis of the characteristics of the resident women alone. If it is, the second step is to explore the extent to which our characterisation of areas plays a role in understanding differences in limiting long-term illness both at the local and district level.
3. Method

3.1. Data source and structure

We took from the ONS-LS datafile 76,374 women aged between 16 and 45 in 1971 (and hence aged 36-65 in 1991 – a 30-year cohort) who had full census records at the three time points. This involved discarding 18% of women in this age group who were matched and traced into the LS in 1991 (when the LLTI question was first included) who were not also present in one or both previous censuses. In a minority of the cases the women are known to be immigrants (ca 5%), but the main reason for omission is linkage failure, i.e. the women’s records could not be matched into the LS or they were absent from the census. Linkage for this age group is at approximately average rates for the whole study (Hattersley and Creezer, 1995). They report in Chapter 5 overall backward linkage rates of 93% from 1981 and 91% for 1991. Typically linkage failure affects the younger adults more than those in later middle age. A further 2% of the 1991 sample were discarded because their census record contained missing data or they were enumerated as a visitor or in a communal establishment. Finally just under 1% (707 cases) with permanent sickness in 1971 or 1981 were also excluded from the analysis, in order to avoid, as far as possible, results being unduly influenced by the high chance certain individuals had of reporting limiting long-term illness in 1991. We note the possibility that housewives who were in very poor health may not have been identified by these questions, which are linked to those on economic activity, and would remain in our sample. The sample was clustered into 9,359 electoral wards nested within 403 county districts. For our sample the average number of women included in a ward is 8 and 191 per county district.

3.2. Limiting long-term illness

The outcome variable in the analysis is LLTI as described above.

3.3. Individual characteristics

In an attempt to explain the level of women’s reported LLTI a number of individual characteristics are included in the model: age,
education, ethnicity, and three summary indicators combining 1971 to 1981 censuses to reflect material circumstances and migration. Car access and home ownership were as reported in 1971 and 1981 by the household. Intercensal migration was defined in terms of the woman’s movement either within or between county districts. Finally, enumeration in the South-East in either 1971 or 1981 was used to account for any potential material benefits of residence in this region on individual circumstances (following Fielding, 1995). A summary table of individual-level variables is shown in Table 1.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Categories</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age in 1971</td>
<td>Measured as continuous variable</td>
</tr>
<tr>
<td>Education</td>
<td>Degree holder in 1971 and/or 1981</td>
</tr>
<tr>
<td></td>
<td>Non degree holder</td>
</tr>
<tr>
<td>Ever resident in the South-East</td>
<td>Lived in South-East in 1971 or 1981</td>
</tr>
<tr>
<td></td>
<td>Lived outside South-East in 1971 or 1981</td>
</tr>
<tr>
<td>Ethnicity</td>
<td>White</td>
</tr>
<tr>
<td></td>
<td>Non-white</td>
</tr>
<tr>
<td>Car access in household</td>
<td>No car in 1971 or 1981</td>
</tr>
<tr>
<td></td>
<td>No car in 1971, car in 1981</td>
</tr>
<tr>
<td></td>
<td>Car in 1971, car in 1981</td>
</tr>
<tr>
<td>Housing tenure</td>
<td>Non-owner in 1971 and 1981</td>
</tr>
<tr>
<td></td>
<td>Non-owner in 1971, owner in 1981</td>
</tr>
<tr>
<td></td>
<td>Owner in 1971, non-owner in 1981</td>
</tr>
<tr>
<td></td>
<td>Owner in 1971 and 1981</td>
</tr>
<tr>
<td>Migration 1971-1981</td>
<td>Same district</td>
</tr>
<tr>
<td></td>
<td>Different district, same county</td>
</tr>
<tr>
<td></td>
<td>Different county</td>
</tr>
</tbody>
</table>

The majority of these individual level variables are categorical. In the modelling results that follow estimates of the fixed effects of being a member of a particular category are given in contrast to a reference category which is always, and arbitrarily, the first named category in the table above. Age was centered on the average age of 29.9 years in 1971.
3.4. Ecological or geographical units of analysis

The second and third level units used in the analysis are respectively, the 9,359 wards and 403 county districts from 1991. Wards were characterised by 5 principal component scores derived from our analysis of 37 variables from the Small Area Statistics. For convenience these components have been labelled as deprivation (poverty versus affluence), area type (educated professionals (along with young children of school age) versus poorer manual families), demographic character (young families versus an older mixed population), settlement (young single people, often in private rented and terraced housing versus middle aged and larger families), and comfort (households with 2 or more cars, central heating (typically in rural locations) versus households with manual heads, a high proportion of working women and use of public transport). At the third level in the geographical hierarchy, county districts are described as belonging to one of twelve homogenous groups based on similarities derived from the 37 individual census items exactly as in Wallace and Denham (1996). The labels used in the ONS area classification and in our analysis are shown in Table 2 together with the number of districts in each group and the average percentage

<table>
<thead>
<tr>
<th>Area classification</th>
<th>Number of districts</th>
<th>% total districts</th>
<th>Mean % LLTI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coalfields</td>
<td>43</td>
<td>10.72</td>
<td>18.0</td>
</tr>
<tr>
<td>Ports and industry</td>
<td>15</td>
<td>3.74</td>
<td>18.4</td>
</tr>
<tr>
<td>Inner London</td>
<td>17</td>
<td>4.24</td>
<td>15.5</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>23</td>
<td>5.74</td>
<td>15.3</td>
</tr>
<tr>
<td>Resort and retirement</td>
<td>24</td>
<td>5.99</td>
<td>12.6</td>
</tr>
<tr>
<td>Mixed economies</td>
<td>37</td>
<td>9.23</td>
<td>12.4</td>
</tr>
<tr>
<td>Mixed urban and rural</td>
<td>44</td>
<td>10.97</td>
<td>12.3</td>
</tr>
<tr>
<td>Services and education</td>
<td>18</td>
<td>4.49</td>
<td>10.6</td>
</tr>
<tr>
<td>Coast and countryside</td>
<td>66</td>
<td>16.46</td>
<td>10.2</td>
</tr>
<tr>
<td>Growth</td>
<td>25</td>
<td>6.23</td>
<td>9.7</td>
</tr>
<tr>
<td>Most prosperous</td>
<td>86</td>
<td>21.45</td>
<td>8.3</td>
</tr>
<tr>
<td>Scotland</td>
<td>3</td>
<td>0.75</td>
<td>7.8</td>
</tr>
<tr>
<td>Totals/overall LLTI</td>
<td>401</td>
<td>100.00</td>
<td>12.9</td>
</tr>
</tbody>
</table>
of LLTI reported for the age group used in our investigation. The extent to which any of these raw percentages are due to differences in the age composition of each cluster of districts by ONS area classification is taken into account at an individual level in subsequent modelling. Age standardized LLTI rates (not shown here) reveal very little difference in the rank ordering of the clusters by observed LLTI percentages.

The areas classified as ‘Ports and industry’ and ‘Coalfields’ have the highest levels of reported LLTI whereas ‘Growth’ and ‘Most prosperous’ areas (and districts labelled ‘Scotland’ with very few districts) have the lowest.

3.5. Modelling strategy

In the exploration of the interplay of person and place in influences on women’s health, multilevel modelling allows both area and individual effects to be represented in a three level population hierarchy. Individual women at level-1 are nested within wards at level-2 and wards are nested within county districts at level-3. By separating out individual and area level characteristics it becomes possible to investigate how variables (our 5 principal component scores) defined at the ward level might affect the prevalence of limiting long-term illness over and above the contribution of a woman’s characteristics. Similarly, the impact of the wider locality (county district) can be examined once the character of the ward and the individual resident’s circumstances has been taken into account. All modelling was implemented by the software package MLwiN (Goldstein et al., 1998).

Formally, the appropriate statistical model for a binary outcome is described as a logistic multilevel regression model (Goldstein, 1991). All model estimation was carried out using the default estimation procedure for non-linear models, namely marginal quasi-likelihood (MQL) followed by predictive quasi-likelihood (PQL) (Goldstein, 1995, Chapter 7). The fixed part of the model is defined by a linear function of both individual and area level explanatory variables. The random part of the model identifies three components of variance: between districts (level-3), between wards within districts (level-2 variance) and that between individual women within wards (the level-1 variance). The inclusion of area level characteristics in the model is equivalent to attempting to model any between-area differences as identified in terms
As age is expected a priori to be a predictor of LLTI status, it has to be included in any model. This simple model is referred to as our base model. It includes a quadratic term for age simply as a conventional device to improve statistical fit. This base model provides estimates of the two variance component estimates for ward differences within districts and between district differences. In terms of our central research question then, our objective is first to see whether or not we can formally identify between-area differences and if so, to see if we can explain any such differences in terms of the characteristics of the individual women who reside there and then the nature of these areas (composition). In modelling terms we proceed sequentially. First, after fitting the base model, we include all individual characteristics in the model and then check, by means of backward elimination of each characteristic in turn, whether or not a statistically significant contribution is made to the model (based on the reduction in the log likelihood, Goldstein et al., 1998, p. 32). For the remaining variables we next test for the presence of interactions at the individual level. The resulting model is described as our interim 1 model (if you prefer, a ‘reduced main effects and interactions’ model). A second interim model is then fitted by attempting to explain any remaining ward level differences (interim 2) by including ward scores at level-2. Finally, the level-3 ONS area classification is included as a dummy variable to reduce any area level variance at the district level. This results in our final model. The results for all three models are presented in Table 3. The interpretation of the modelling follows two strands. Firstly, the interpretation of the fixed part of the model and its ability to explain differences between areas. Fixed effects can be thought of as representing a typical or average effect of individual variables such as ethnicity, or the impact of the character of the area itself, on the risks of reporting LLTI across the whole sample. Secondly, district level residuals are mapped at each stage of modelling to reveal the extent to which any district has an excess of ill health or ‘good’ health. The small number of women observed in any ward mean that mapping ward level residuals would be unreliable.
Table 3  
Baseline, interim and final models for LLTI as a binary outcome  
for 76,374 women aged 16-45 in 1971  
nested within 401 county districts in England and Wales  
(standard errors are given in parentheses)

<table>
<thead>
<tr>
<th>Terms</th>
<th>Base model</th>
<th>Interim model 1</th>
<th>Interim model 2</th>
<th>Final model</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fixed effects</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Individual (level-1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-2.138 (0.025)*</td>
<td>-1.825 (0.086)*</td>
<td>-1.847 (0.085)*</td>
<td>-1.656 (0.097)*</td>
</tr>
<tr>
<td>Age</td>
<td>0.072 (0.002)*</td>
<td>0.068 (0.004)*</td>
<td>0.068 (0.003)*</td>
<td>0.068 (0.003)*</td>
</tr>
<tr>
<td>Age²</td>
<td>-0.001 (0.000)*</td>
<td>-0.001 (0.000)*</td>
<td>-0.001 (0.000)*</td>
<td>-0.001 (0.000)*</td>
</tr>
<tr>
<td>Not in South-East in '81 or '91</td>
<td>0.275 (0.033)*</td>
<td>0.118 (0.031)*</td>
<td>0.092 (0.035)*</td>
<td></td>
</tr>
<tr>
<td>No degree</td>
<td>0.371 (0.074)*</td>
<td>0.315 (0.075)*</td>
<td>0.313 (0.075)*</td>
<td></td>
</tr>
<tr>
<td>Non-white</td>
<td>0.683 (0.066)*</td>
<td>0.597 (0.067)*</td>
<td>0.609 (0.068)*</td>
<td></td>
</tr>
<tr>
<td>Cars (linear effect)</td>
<td>-0.204 (0.011)*</td>
<td>-0.172 (0.011)*</td>
<td>-0.170 (0.011)*</td>
<td></td>
</tr>
<tr>
<td>Owner occupier in '71 and '81</td>
<td>-0.436 (0.025)*</td>
<td>-0.357 (0.026)*</td>
<td>-0.363 (0.026)*</td>
<td></td>
</tr>
<tr>
<td>Interaction</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cars * Age</td>
<td>0.004 (0.001)*</td>
<td>0.004 (0.001)*</td>
<td>0.004 (0.001)*</td>
<td></td>
</tr>
<tr>
<td>Ward (level-2)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poverty/affluence score</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Area type score</td>
<td>-0.092 (0.013)*</td>
<td>-0.086 (0.014)*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Demographic score</td>
<td>0.034 (0.013)*</td>
<td>0.037 (0.014)*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>County district (level-3)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>'Scotland'</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coastal</td>
<td>-0.769 (0.303)*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mixed urban and rural</td>
<td>-0.280 (0.060)*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Growth</td>
<td>-0.183 (0.057)*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Most prosperous</td>
<td>-0.240 (0.055)*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Services and education</td>
<td>-0.285 (0.082)*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Resort and retirement</td>
<td>-0.230 (0.079)*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mixed economies</td>
<td>-0.115 (0.076)*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Manufacturing</td>
<td>-0.249 (0.060)*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ports and industry</td>
<td>-0.125 (0.059)*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inner London</td>
<td>-0.136 (0.059)*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Random effects</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Individual</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>Ward</td>
<td>0.096 (0.017)</td>
<td>0.036 (0.015)</td>
<td>0.021 (0.014)</td>
<td>0.018 (0.014)</td>
</tr>
<tr>
<td>County district</td>
<td>0.119 (0.013)</td>
<td>0.049 (0.008)</td>
<td>0.011 (0.04)</td>
<td>0.009 (0.004)</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>30,757.8</td>
<td>27,529.1</td>
<td>26,641.7</td>
<td>26,718.4</td>
</tr>
</tbody>
</table>

* Significantly different from zero at 95% confidence.
4. Results

4.1. The interplay of individual and area level differences

The estimates for fixed and random effects are given for each of the four stages of modelling in Table 3. The models are labelled \textit{base}, where age terms are the only individual characteristics included in the model; \textit{interim 1} which includes individual characteristics (or reduced and relevant interaction terms) in addition to the age terms; \textit{interim 2} which begins to model area variation by including ward scores at level-2; and fourthly, the \textit{final} model completes the list with a categorical variable to describe the classification of the county district at level-3.

4.2. Random effects

Once we take account of a woman’s age there are still differences between areas at both the ward and district levels. These estimates of area differences are variances of the estimated residual terms associated at each level. Here a level-2 variance of 0.096 for ward differences and a level-3 variance of 0.119 for districts, which are both statistically significant. In terms of our research question the challenge now is to see to what extent the inclusion of further terms, first about the woman and then about the localities, can explain these differences.

The inclusion of individual level characteristics at level-1 reduces the variance component at level-2 by almost two-thirds (a reduction of level-2 variance to 0.036 in interim model 1) as well as marking a dramatic reduction in the level-3 variance (by 59% to 0.049). Thus area differences at both the ward and district levels decrease convincingly once we take account of the characteristics of the women who make up the local populations. We will return to this observation in our analysis of district level residuals below, and to the individual predictors of women’s health as described below. What further gains are there in the reduction of area differences if we now explore the impact of including the ward characteristics? Of the original 5 ward scores described earlier only three achieve any significance in the model. The addition of the ward scores in our interim model 2 achieves a successive reduction in the variance at both levels (42% to 0.021 for wards and 78% for county districts from 0.049 to 0.011). For the final model, which includes the ONS classification, we hardly see any further variance reduction.
4.3. Fixed effects

Women’s individual circumstances provide an important explanation of between area differences. The base model confirms a positive relationship between a woman’s age and her probability of reporting a LLTI. The age quadratic term suggests stronger effects as age 65 approaches. Being non-white, without a degree (the only level of qualifications distinguished in the census), and not recorded as residing in the South-East, all contribute to increased risk of women reporting LLTI. Further, being without access to a car in ’71 and ’81 and/or not being in owner occupancy for these time points also increases this risk. In Table 3 car access is reported as a linear effect. Thus the categories presented in Table 1 for car access can be read as an arithmetic scale from 0 to 3. Housing tenure is reported as a dichotomous variable as the fixed effects estimates for categories distinguishing between different states of owner occupancy in 1971 or 1981 were not very different. The migration history variable was non-significant and it is not included in Table 3. The only significant interaction term to remain at the individual level was the joint effect of car access and age. It could well be that car access for older women becomes a necessity as a result of their health status. At an area level the nature of the immediate locality has an effect on the risk attributed to individual circumstance. Notably, living in a poor ward and/or a ward where there is a preponderance of young families increases risk of poor health over and above a woman’s characteristics. Being in a ward where there are a large number of educated families with young children will reduce that health risk for a woman. At a district level, being in any district other than a (former) Coalfield (the reference category) reduces individual risk. If anything, living in a district classified as a Resort and Retirement, Manufacturing or Port and Industry puts women closest to those with similar circumstances living in the Coalfields. This group stands in contrast to those living in districts described as ‘Most prosperous’ or ‘Growth areas’. However, it must be noted that whilst the district classification produces a fine tune on individual health risk it does not provide much by way of further explanation of between-area differences. The locality as described by the ward has a greater impact.

Allowing the fixed effects to vary within areas revealed no evidence of any differential effects. Our interpretation of the fixed part of the model is, therefore, reliable across different types of area.
4.4. Residual analysis to confirm our model interpretation

This section replicates an analysis of district level residuals reported for men (Wiggins et al., 1998). Any examination of ward level residuals was ruled out, as each estimate would only be based on a few women (typically <10). Figure 1 maps the distribution of %LLTI at a district level for women prior to any analysis. A ‘North-South divide’ line has been imposed on the maps following Sloggett and Joshi (1994). There are more ‘pockets’ or concentrations of higher levels of reported LLTI in the North compared to the South but there is not a clear divide. There are notable concentrations of high %LLTI in districts located in Inner London, the South-West and the Isle of Wight.

An exploration of district level residuals enables us to examine what happens to the pattern of outliers as we systematically take account of information about the characteristics of women, their neighbourhoods and surrounding districts. A district level residual marks out the extent to which any excess or deficit of reported LLTI is observed at each stage of the modelling. A residual, which is described as having more reported LLTI than is predicted by multilevel regression, is an ‘unhealthy’ district. Whereas a residual, which has less reported LLTI than is predicted by the model, will convey the opposite ‘healthy’ effect of area. Residual plots are presented in Figures 2 and 3 below. Any residual, which is not plotted, simply includes zero in their 95% confidence intervals.

Taking account of the age distribution of women (our base model) explains a lot of the district level variation in rates of reported LLTI. Those districts that remain as outliers throw the North-South divide into sharp focus. Only two districts in the South (one Inner London Borough and one area on the outskirts of West of London in Berkshire) report higher levels of expected LLTI, whereas the majority of excess levels of reported LLTI are north of the divide. Indeed, it is only in the South-East and South-West that we see health benefits. How does the picture change as we take account of women’s individual circumstances?

Firstly, the number of significant residuals is reduced considerably. Our account of individual circumstances has done a lot to explain healthy area effects at the district level. The persistent unhealthy districts remain in parts of the North West, North and East and South Wales. A solitary healthy district stands out in the South (an outer
Figure 1
% LLTI for LS women aged 36-65 years in 1991 by county district
Figure 2
Outlier county district residuals for base model
for LS women aged 36-65 years in 1991

Less limiting longterm illness than expected
More limiting longterm illness than expected

“North-South divide”
Figure 3
Outlier county district residuals for interim model 1
for LS women aged 36-65 years in 1991

Less limiting longterm illness than expected

More limiting longterm illness than expected

"North-South divide"
London Borough). Once we introduce ward scores to characterise the
neighbourhoods into the model these disparities largely disappear from
the map. Providing further confirmation that spatial differences in re-
ported LLTI for women can be largely accounted for by taking account
of individual and local circumstance. Thus the scope for providing
more visual displays of residuals ends with interim model 1. Whilst
broader regional differences do affect the overall risk for the individual
they do not add very much in terms of explaining the area differences
reported in the raw data. Finally, the value of the log likelihood re-
ported in Table 3 suggests that we are not strictly seeing a steady im-
provement in statistical fit beyond interim model 2. If anything the
values are broadly similar between interim model 2 and the final model.

5. Discussion

For the first time this century in England and Wales with the in-
clusion of a question of limiting long-term illness in the 1991 Census it
has been possible to observe the pattern of geographical variations in
LLTI (Charlton and Wallace, 1994).

We have been able to pioneer the multilevel analysis of individual
records in the ONS-LS. Earlier work (e.g. Congdon, 1995; Duncan et
al., 1993; Shouls et al., 1996) has emphasised the importance of multi-
level framework to better understand geographical variations in LLTI.
Despite differences in the degrees of geographical clustering and cov-
erage our findings are in broad agreement. Gould and Jones (1996)
conclude that the variations between SAR areas remain substantial
even when individual characteristics are taken into account. Unlike
Congdon (1995) and Shouls et al. (1996) they did not attempt to model
or explain between-place variation. Shouls et al. (1996) provide evi-
dence of a stronger ecological effect for men than for women as well
as for the interaction between individual and area level characteristics.
From their interpretation it would appear that the differences between
more and less deprived individuals are marked in affluent areas, rather
than in more deprived areas. In future work we plan to explore similar
interactions to better understand the interplay between individual and
area level characteristics.

We have found that cars and home ownership were useful markers
of social and material advantage apparently protecting against the risk
of reporting LLTI. Migration into or living in the South-East region
appeared beneficial, but otherwise there was not much effect of moving home. After also adjusting for a woman’s individual circumstances (education and ethnicity), county district differences persist. It appears that almost all of the remaining area differences are explained by the social profile of wards in these areas. Whilst living in a (former) Coal-field does increase the individual health risk it does less in terms of accounting for area differences. This represents a notable difference in the finding for men (Wiggins et al., 1999), where the ONS classification reduced the district level variance by nearly a half once ward scores were added to the model. For women the equivalent relative reduction is less than a fifth (0.011 to 0.009). For men, the majority of county districts with a high level of unexplained reported rates of LLTI are largely classified as Coalfields (past or present). This suggests two possible interpretations. The first is that the health of men in these places was more directly affected by the mining and heavy industrial activity because they were more likely to have been involved themselves in potentially harmful activities. However, we did find stronger geographical differentials for men in analyses which made some allowance for individual occupations.

Another interpretation, which could also complement the first, is that the reporting of limiting long-term illness is socially as well as biologically gendered. The concept presupposes a notion of a normal level of activity. In a context where local industrial change has removed many of the traditional employment opportunities for men, but less so for women, more men will find themselves unable to find employment. In other geographical contexts these men might otherwise be employed. Under these circumstances it is not clear whether supply or demand limits activity. The fusion of long-term unemployment and long-term ill health is compounded by the effect of morale and a sense of control (Wilkinson, 1996) on health and by specific gendered institutions in the British social insurance and support system.

The bureaucratic confirmation of a long-term sick status was much more likely to apply to men than to women. The term ‘unemployment’ is often associated with drawing benefit. There are two reasons why the benefit system tends not to treat married women and claimants in their own right. For most of this period, most married women opted out of National Insurance in their own right, relying on their husband’s insurance. This option started to be phased out in 1977. Even after that, married women could not make claims for means tested benefits except as a couple. During the 1980s the benefit
system started to treat many (particularly male) claimants in their 50s and 60s as invalidity pensioners rather than unemployed. As women’s perceptions of what they would normally be expected to do would cover domestic work and different sorts of employment from men’s, there is a limit to which we can make direct pronouncements on gender differences in the individual propensity to report LLTI. We generally find more variability in LLTI for men at the district, or local labour market level than women. By the 1980s geographical variations in women’s employment participation in Britain had become relatively minor, but traditionally (i.e. up to the 1970s) it had tended to be low [in the regions] where men’s long-term illness tended to be high, particularly districts associated with mining and heavy industry. This applies particularly to South Wales, but a notable exception is the high female employment in the textile towns of the North-West (see Joshi and Hinde, 1993; Ward and Dale, 1991; Joshi, 1984). Thus if areas with the highest levels of reported male LLTI were also (to some extent) areas with the greatest differences in the gender division of paid labour, and of lifestyle, this could give rise to the differential geographical patterning by gender. We cannot however exclude the possibility that what we are seeing is a gender difference in a set of reactions to industrial decline. For men, in the affected labour markets, this is more manifest as the reporting of limiting long-term illness than it is for women. We can draw support for there being economic influences on reporting from our other analyses on current morbidity reported in survey data (Mitchell et al., 2000).

6. Conclusion

The use of multilevel modelling has enabled us to analyse the risks of women aged 16-45 years in 1971 reporting LLTI in 1991 in a framework that divides area variation into two distinct components: that between localities (wards) within county districts and that between districts themselves. The modelling recognises the clustering of women’s residential location by defining a population hierarchy based on administrative boundaries. These areas convey the role of geography, and the resulting social and economic characterisation of areas, in explaining illness reporting. In particular, any evidence for a ‘North-South divide’ in reported LLTI for women can be largely explained by
the variables measuring characteristics of individuals and wards, which we have been able to include.

Blane et al. (1996) suggest that illness behaviour is shaped by the social environment and reflects the impact of disease on the ability to carry out social roles. What we have been able to show for women, as well as men, is that a set of variables reflecting material circumstances at the individual level: car access and home ownership, education, ethnicity and observation in the South-East help to explain the regional variation in reported illness, but not completely. Prevalence of LLTI also varies between localities defined by their social profile, even for women with similar individual characteristics. Most important is the influential role of aggregated ward characteristics for women’s health over and above these individual similarities. Characteristics of the local economy, which do relate to variations in men’s reported illness are less relevant to women. Where a woman lives matters much more in terms of her local neighbourhood than the wider socio-economic landscape.

Acknowledgements

This paper forms part of the programme of work of the ESRC Health Inequalities Programme: Dimensions of Health Over Persons, Time and Place (Grant No. L12851012). The authors also gratefully acknowledge the permission of the ONS to access the Longitudinal Study, and their assistance with initiating the use of multilevel modelling on their computers.

References


PLACE AND PERSONAL CIRCUMSTANCES


CMU (1993), *A User Guide to the SARs* (2nd ed.), Census Microdata Unit, Faculty of Economic and Social Studies, University of Manchester.


