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Chapter 23

Using 2011 Census Data to Estimate Future Elderly Heath Care Demand

Stephen Clark, Mark Birkin, Alison Heppenstall and Philip Rees

Abstract

There is recognition by health planners and academics that the ageing of populations has the potential to place growing demands on health services, and that this pattern of demand will vary by place. This chapter outlines how the 2011 Census aggregate outputs, together with microdata from the English Longitudinal Study of Ageing (ELSA), have been used to estimate the demand placed on the health services in each English local authority district to 2031, focusing on three specific morbidities. The morbidities studied are cardiovascular disease (CVD), diabetes or high blood sugar (DHBS) and respiratory illnesses (RI). Together, these three morbidities are the primary cause of nearly half the deaths in those aged 50 and older. The Census 2011 data also provide inputs for the sub-national population projections and for the revision of 2001 Census based local ethnic projections. Without these Census data, the spatial scale for this modelling would need to be regional at best and local variations would be absent, making future resource planning difficult.

23.1 Introduction

Many western societies are predicting an important shift in the composition of their populations. The clear historical and anticipated future trend is for the elderly population to increase, both in numbers and as a proportion of the total population (Rechel et al., 2009; European Commission, 2014). For England, the latest 2014-based principal projection by the Office for National Statistics (ONS, 2015) shows the English population aged 50 and older increasing from 19.4 million in 2014 to 24.8 million in 2034, a gain of 5.4 million. This is in the context of a more modest increase of 2.1 million in the 49 and younger population.

The question arises as to what this ageing phenomenon will mean for society at large (Rutherford, 2011; House of Lords, 2013). Whilst longer life expectancies are to be celebrated, the ageing of the population is, at best, seen as a challenge (Christensen et al., 2009) and at worst, a threat (Laurence, 2002). But, in terms of provision of services for an ageing population, health is an area where the impact of an ageing population will be most keenly felt (Wanless, 2004; Craig and Mindell, 2005). Here, the composition of this projected population will be important and questions arise around its economic, social and cultural composition. For example, the ethnic composition of the ageing population may change over time, with a trend towards greater diversity; the lifestyle history of the population will evolve, with downward trends in smoking and rising obesity; and the employment history will continue to transition away from manual occupations such as mining, steel and textiles towards retail and service occupations. Since health care planning and delivery are carried out at the local level, it is also important to gain an understanding of the changes in the geographic distribution of this demand.

23.2 Determinants of health care

The health care demands associated with an elderly population and the determinants affecting this demand are intensively studied. Some research examines the prevalence of specific morbidities (Seshamani and Gray, 2004); other work looks at either general health or the presence of limiting activities (Lubitz et al., 2003). Many studies, particularly from North America, model health care costs as a proxy for ill health (Denton et al., 2002). The general findings are that as people get older they are more prone to develop morbidities or be in generally worse health. This means that, all other things being equal, an older population will tend to have worse health (Alemayehu and Warner, 2004). However, chronological age itself may not be the actual driver of health status. Some studies have reported that it is the remaining years of life that are important, with an individual's health deteriorating in the final months or years before death (Zweifel et al., 1999). Others take the argument further and suggest that it is not age or the remaining years of life that are important but the presence of a disabling condition (de Meijer et al., 2011).

Gender and ethnic differences influence health status as well. Females live longer than males but these extra years are not necessarily spent in good health. In regards to ethnicity, there are some morbidity conditions that are more prevalent within certain ethnic groups, e.g. diabetes is more prevalent in the south Asian population (HSCIC, 2005). A person's socio-economic status, measured using income, wealth, education or employment indicators, can also influence health (McCulloch, 2011).

A range of data exists to study the health outcomes for an aged population. Population censuses provide extensive coverage of the characteristics of the population and provide rich detail on the many determinants often cited as important for health outcomes. However, the actual information collected in the census on health is general and rarely touches on specific morbidities. In addition, the time interval between censuses can be long. To try and overcome these issues, governments often commission national sample surveys that can either be general in nature or targeted on a particular public policy issue, such as health. In an era where administrative systems are increasingly being implemented and coordinated, scope has arisen to use such data for researching health status.

The literature identifies two main approaches used to model elderly health care demand, either statistical modelling or simulation. Statistical modelling is the approach most often used (see Brailsford et al., 2009, for a review of such methodologies). The advantage of this approach is that it is grounded in statistical theory, which allows for various interpretative and testing regimes to be followed. The disadvantage is that statistical modelling is rigid in both its outcome and the reliance on the assumptions that underlie the modelling technique. Just as are there many statistical techniques which can be used, there is also a wide variety of simulation methods. These methods attempt to replicate the composition or behaviour of a population, either real or hypothetical. They commonly use the technique of Monte Carlo simulation to replicate a decision-making process within the simulation system (Brailsford, 2007). The advantage of such an approach is that the simulation can be built using information on the processes being simulated or by simple rules informed from an understanding of the dynamics of health care. However, the drawback is that it is sometimes difficult to disentangle these dynamics, particularly when unexpected or little understood interactions occur.

23.3 The 2011 Census and health

Questions on health are a fairly recent addition to the UK censuses, starting in the 1991 Census with a question on whether the individual considered that he or she had a long-term illness which limited their activities. A question on self-assessed general health was added in the 2001 Census, using a three-point scale of “Good, Fairly good or Not good”. Also in 2001, a question was asked about the amount of time devoted to caring for family members, neighbours or friends.

Prior to the 2011 Census, the ONS conducted a consultation exercise on the health questions in the census (ONS, 2010). There was strong support for retaining the health questions in the census and for continuity so that long-term trends could be assessed. There was, however, scope for some changes. The question on the presence of a limiting long-term illness (LLTI) was expanded from a binary “yes or no” response to a “no, limited a little or limited a lot” response. The general health question was expanded from a three-point to a five-point scale. The question on the amount of caring provided question remained unchanged from 2001.

The UK censuses are therefore able to capture the variations in self-rated health in a population, at geographic scales that vary from small areas to countries. What the censuses do not provide are any details on which specific conditions or morbidities cause individuals to assess their health as less than good. For general health planning and the allocation of resources, these general measures may be sufficient, but more detailed local health planning information on which morbidities are present are of greater value. This information could then influence the relative allocation of resources to various sectors of the health system, e.g. to local pharmacies, general practitioners, hospitals or specialist treatment centres. Whilst surveys are available that begin to capture this detail of information, they are not comparable to the census in being able to provide the geographically specific information. What is therefore required is a way to combine the rich geographic details of the census with the information rich detail contained in these surveys.

23.4 Spatial microsimulation

A technique that is often used to achieve this goal is spatial microsimulation. The technique attempts to reconstruct a population of individuals for a specific area from a sample population. Individuals are chosen, with replacement, from this sample population, based on a comparison of their individual characteristics and the known aggregate characteristics of the population of the area. Thus, if an area contains a count of 200 individuals who are male, aged 55 to 59 and of Chinese ethnicity, then the task is to repeatedly select individuals from the sample population to meet this constraint. The spatial microsimulation task is to estimate a set of area-specific weights to apply to the sample population so that, when the sample population is aggregated using these weights, they reproduce the aggregate constraint counts. Spatial microsimulation has been used widely in the field of health (Brown, 2011). This technique is able to produce synthesised local populations which may then be used in further modelling exercises. Applications in the area of health planning have included morbidity prevalence estimates (Clark et al., 2014; Shulman et al., 2015), the prevalence of obesity (Edwards et al., 2011), people who smoke (Smith et al., 2011) and care needs (Lymer et al., 2009).

Immediately the value of the census tabulations becomes apparent in that they are able to provide the constraint count tables. These counts are very accurate estimates for small areas and are flexible in the range of multi-dimensional cross-tabulations that are possible. Hermes and Poulsen (2012) recommend using such multi-dimensional tables as constraints in spatial microsimulations and the Detailed Characteristics and Local Characteristics tables from the 2011 Census are ideally suited to this purpose.

Attention then turns to a source for the individual microdata to be sampled. The microdata outputs from the 2011 Census are not suitable since they do not add any extra information. There are, however, some government surveys that may be of value. These include the Health Survey for England (HSfE) (Joint Health Surveys Unit, 2012) and the English Longitudinal Study of Ageing (ELSA) (Institute for Fiscal Studies, 2015). The HSfE is able to provide a detailed picture of the health of the English population and also trends in various health related activities, e.g. smoking, drinking, gambling and physical activity. Since the HSfE is a general health survey, it is not able to give particular prominence to sub-sections of the population, although there are occasional one-off survey boosts to the survey to highlight for example, the health of ethnic minorities, young people or the elderly. Of particular concern to a study of the elderly population is that the HSfE does not include in its sample residents in communal establishments such as residential or nursing homes. Outputs from the 2011 Census show that, particularly for the very old, such residents are a substantial part of the elderly population.

The ELSA is a survey that is particularly geared to gaining an insight into the lives of the elderly population of England. The purpose of the survey is to examine the life histories of the ageing population of England in order to better understand the impact of both ageing and the passage of time on health. ELSA data are not limited to physical and psychological health outcomes but include a wide range of objective and subjective measures about the respondents and their households, including work and pensions, income and assets, housing and social participation. ELSA participants are aged 50 or older and at each biennial survey wave attempts are made to contact the same individuals. The ELSA asks the same range of questions at each wave and questions about morbidities associated with an elderly population are given particular prominence. The feature of the ELSA that makes it particularly suitable as a sample population is that it surveys individuals who have moved into a communal residential setting.

Candidate constraints

Anderson (2007) sets out four criteria for the selection of suitable constraints for a spatial microsimulation:

1. compatibility of definition in the constraint and sample populations;
2. availability for the unit of analysis (in his case, households, but here individuals);
3. reasonable predictive power at the small area level; and
4. good predictive power at the unit of analysis level.

Here, a joint consideration of criteria two and three is used to identify a long list of candidate constraint variables, which is then refined in light of the first and fourth criteria. Examination of the literature suggests that there are differences in health outcomes by age, with ill health becoming more common at older ages. Gender can also influence health outcomes. It is likely that the presence of a morbidity condition will cause a person to assess his/her own health as either “not good” or as “limiting their activities”. Individuals from certain ethnic groups have differing health profiles for some morbidity conditions. Someone who is cohabiting or in a relationship has better health outcomes compared to someone who has always lived alone or who is separated or widowed. The socio-economic status of the individual needs also to be taken account of. This can be measured directly using the individual’s socio-economic status classification (NS-SeC) (Rose et al., 2005) or indirectly using information on the tenure of the household in which they live (as a proxy for wealth), the level of highest qualification (as a proxy for both wealth and income) or through the level of vehicle ownership (as a proxy for both income and mobility). These variables therefore emerge as candidate constraints under criteria two and three. A detailed examination of the 2011 Census and the ELSA wave 5 variables demonstrates that variables with similar definitions in both data sets can be identified. This satisfies Anderson’s first criterion, leaving the final criterion, the performance of the variable in predicting the outcome of interest, to be considered.

Anderson tackled the fourth criterion using an incremental series of nested binary logistic regressions with a succession of candidate explanatory variables. Here a similar approach is used by estimating three hazard models, a form of logistic regression (Singer and Willet, 2003), one each for the presence of cardio vascular disease (CVD), diabetes or high blood sugar (DHBS) and respiratory illness (RI), and testing the suitability of each constraint variable. In order of importance, the hazard models identified the presence of a limiting long term illness, age, gender and ethnicity as important socio-demographic influences on the incidence of the three morbidities (ethnicity was particularly influential on diabetes). Of the candidate socio-economic variables, living arrangements, car ownership and NS-SeC were influential for the morbidities. The influences of tenure, education qualification and the amount of care giving were found to be poor. The results of the hazard modelling suggest that the 2011 Census tables shown in Table 23.1 could be used as possible constraints.

Tables DC1117 (age and gender), DC2101 (ethnicity) and DC6114 (NS-SeC) are based on the usual resident population, which is the population under study. Tables LC3101 (disability), DC1108 (living arrangements), DC4109 (vehicle ownership) are based on those resident in households, which is a subset of the usually resident population. The remaining table DC3402 (disability) is based on those who are resident in communal establishments. It is desirable to have a consistent population in all the constraint tables; here the residential population of the area. (This is possible with 2011 Census counts since they have not been subject to post-tabular disclosure control, see Stillwell and Duke-Williams, 2007, for its impact on 2001 Census outputs). This consistent population is achieved by identifying a 'residual' population in each local authority district (LAD) in the household and communal establishment residential populations about whom nothing is known other than their 'otherness' in regard to the substantive population of the table. Thus, if the level of household vehicle ownership is known for 1,000 residents in households in the LAD and the usual residential population of the LAD is 1,100 then a residual category of 'communal' is created in table DC4109 with a count of 100 about whom no vehicle ownership is known. Similarly, if there are 100 communal residents in the LAD whose disability status is known in table DC3402, a category of ‘household’ is created in this table with a count of 1,000. Since these residual categories now exist in the tables, it is necessary to provide individuals in the sample population with these residual characteristics who can be sampled. So for example, this is achieved by associating the level of vehicle ownership for a sample individual who is resident in a communal establishment as ‘residual’ (i.e. unknown).

Table 23.1 Census 2011 tables which are candidates to serve as constraints for the microsimulation model

Table	Age bands	Categories
DC1117 (Age structure)	Single years of age	Not applicable
LC3101 (Disability) *	50-54 55-59 60-64 65-69 70-74 75-79 80-84 85 and older	Limited, not limited
DC2101 (Ethnicity)		English/Welsh/Scottish/Northern Irish/British, Irish, Gypsy or Irish Traveller, Other White, White and Black Caribbean, White and Black African, White and Asian, Other Mixed, Indian, Pakistani, Bangladeshi, Chinese, Other Asian, African Caribbean, Other Black, Arab, Any other ethnic group
DC1108 (Living Arrangements) *		Married couple, Cohabiting, Single, Married (not a couple), Separated, Divorced, Widowed
DC4109 (Vehicle ownership or use) *		No vehicle, one vehicle, two or more vehicles
DC6114 (NS-SeC)	50-64 65 and older	1.1 Large employers and higher managerial and administrative occupations, 1.2 Higher professional occupations, 2. Lower managerial, administrative and professional occupations, 3. Intermediate occupations, 4. Small employers and own account workers, 5. Lower supervisory and technical occupations, 6. Semi-routine occupations, 7. Routine occupations, 8. Never worked and long-term unemployed, L14.1 Never worked, L14.2 Long-term unemployed, L15 Full-time students
DC3402 (Disability) +	65 to 74 75 to 84 85 and older	Limited a lot, limited a little, not limited, staff member, family member

Notes:
* The population base is residents in households.
+ The population base is residents in institutional establishments.

The Flexible Modelling Framework (FMF) software package is used to derive the LAD-specific spatial weights (Harland, 2013). This implementation of spatial microsimulation uses the combinatorial optimisation approach (Voas and Williamson, 2000). In this approach, an objective function is defined that measures how well the weighted aggregate counts in the sample population agree with the constraint counts in each constraint table. Commonly, the Total Absolute Error (TAE), which measures the absolute value of the difference between the weighted aggregate counts and the census tabulated counts, is chosen as both the objective function and a measure of goodness-of-fit. Rather than use all seven constraint tables in the weight estimation process, only five are used, with vehicle ownership and NS-SeC held back for validation purposes.

To derive the spatial weights for a population of just over 18 million people, the FMF takes 12 hours on a quad core i5-2300 PC with 4GB of RAM running Windows 7. The outputs of the FMF are contained in two files: a sample weights file that contains pairs of zone identifiers (the LAD codes) and sample member identifiers (ELSA participant codes) and a statistical fit file that reports the TAE at the end of each annealing stage for each LAD. The average final TAE value is just 39 and the largest is 272 for Birmingham. This means that just 272 of the 292,565 individuals aged 50 and older living in Birmingham (0.093%) have been miss-allocated to one of the constraints across all five constraint tables.

Prevalence estimates for 2011

As well as the constraint variables that correspond with 2011 Census variables, the ELSA also contains information about the individual that has no equivalent in the census, such as the morbidity status of the individual. Using the LAD specific spatial weights estimated by the FMF and knowledge of which individuals in the sampling population have a morbidity condition at wave 5, it is possible to estimate the number of individuals in each LAD with a morbidity condition and also the prevalence rate. Table 23.2 reports the 10 LADs with the highest estimated prevalence rates and the 10 LADs with the lowest, along with their 2001 ONS area classification type (ONS, 2003).

Table 23.2 Highest and lowest LADs for prevalence of CVD, DHBS, RI or CVD and RI combined, England, 2011

For those LADs with high CVD prevalence rates, there is a range of LAD types. Some LADs will have a population which is generally in poorer health, the causes of which could be employment history or lifestyle factors (e.g. Tendring, a depressed coastal district). Another explanation could be the ethnic makeup of the area, with some ethnic groups tending to have a higher prevalence of the conditions that contribute to CVD (e.g. Tower Hamlets with a large Bangladeshi population). A final explanation could be related to a generally aged population living in the area, with the incidences of CVD accumulating in an older age structure (e.g. Eastbourne). For DHBS, the most important defining characteristic is the ethnic composition of the LAD, with all the top 10 LADs having a high proportion of their population from the black and minority ethnic (BME) community, in particular from the south Asian groups, which tend to have higher rates of diabetes than the general population. With RI, there appears to be both an ethnic and deprivation dimension to those LADs in the top 10, indicating that this morbidity affects individuals differently depending on their ethnicity or deprivation. The LADs with the highest prevalence for the comorbidity of CVD and DHBS appear to be those most impacted by DHBS prevalence, with very similar LADs featuring in the top 10 for both DHBS and CVD and DHBS.

The spatial pattern for the 10 LADs with the lowest prevalence rates appears clearer than for the 10 highest. The vast majority of LADs are prosperous authorities located in southern England, but there are also some London boroughs reporting low prevalence rates. The very diverse and cosmopolitan nature of these boroughs can lead to divergence in the expected outcomes for some morbidity conditions. A case in point is the London borough of Southwark which has the lowest estimated prevalence rate for RI and a low prevalence for CVD. Southwark is an authority with a large black African and Caribbean population (in the 2011 Census, these ethnic groups make up 17% of the 50 and older population). The HSCIC report (2005) shows that illnesses of the heart and circulatory and respiratory systems are lower for these ethnic groups than for the general population. In other Cosmopolitan London boroughs with a very different ethnic mix (say a larger south Asian population), a different prevalence profile is relevant and this is borne out by an inspection of the top 10 prevalence rates in Table 23.2.

23.5 Prediction framework

The framework for producing predictions of these prevalence rates is shown in Figure 23.1. The top half of this figure, the spatial microsimulation to estimate a base 2011 population of individuals in each English LAD, has already been described.

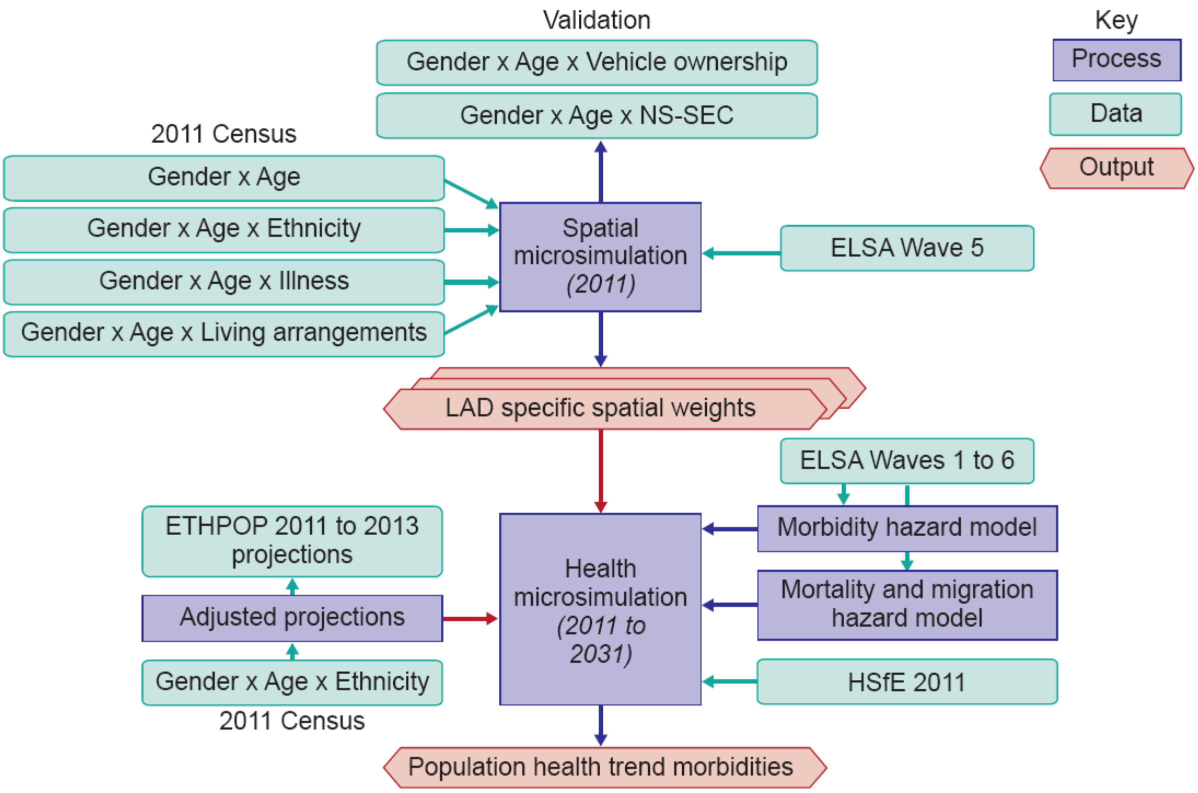

Figure 23.1 The framework for predicting future numbers of people with particular morbidities

Future ethnic composition

In projecting the morbidity status of the population into the future, it is necessary to take account of the demographic composition of the population. The composition of the 50 and older population in each LAD will be influenced by those turning 50 years of age each year, those who die and those who migrate in and out of the LAD. In this framework these population dynamics are captured by use of an external population projection. The ONS provides population projections that estimate the size of the population in each LAD by gender and single year of age but include no other characteristic (ONS, 2014b). However, there is available another set of population projections that provide an additional ethnic breakdown of these populations (Rees et al., 2011; 2012; 2013). These ETHPOP projections are based on information collected in the 2001 Census and subsequent vital statistics on births, death and migration up to 2008, but crucially the projections preceded the 2011 Census. When 2011 Census counts were published, a comparison of the ETHPOP projected population for 2011 with the 2011 Census population indicated a need for revision of the projections (Rees et al., forthcoming). For this study, the ETHPOP projections were updated using a methodology based on that described in Rees and Clark (2014). The steps were:

Step 1. Re-base projections to 2011 Census counts.
Step 2. Utilise subsequent ETHPOP cohort projections.
Step 3. Incorporate a projection adjustment factor based on 2001 to 2011 performance.
Step 4. Constrain the population by gender and age to ONS 2012 subnational mid-year population projections.

The annual projection adjustment factor is calculated from:

$$\text{Yearly adjustment} = \left[\frac{\frac{\text{2011 Census}}{\text{2001 Census}}}{\frac{\text{2011 ETHPOP}}{\text{2001 ETHPOP}}}\right]^{\frac{1}{10}} \tag{23.1}$$

where ‘2001 Census’ is the ethnic specific count of the older population in the LAD from the 2001 Census (Table S101); ‘2011 Census’ is the ethnic specific count of the older population in the LAD from the 2011 Census (Table DC2101); ‘2001 ETHPOP’ is the mean of the TREND-EF and UPTAP-ER 2001 projections of the older population in the LAD from ETHPOP; and ‘2011 ETHPOP‘ is the mean of the TREND-EF and UPTAP-ER 2011 projection of the older population in the LAD from ETHPOP.

This annual adjustment factor captures how the ETHPOP projection needs to be adjusted to reproduce the 2011 outcome (see Table 23.3 for an example). Where the counts are small numbers (which is possible for LADs with small ethnic minority populations), the range of this adjustment is controlled to lie within an empirically derived credible interval calculated on the annual projection adjustments used in other similar LADs.

Table 23.3 Yearly adjustment for the White population of Plymouth

White	2001	2011	Growth	Yearly adjustment
Census	110,314	120,221	$\frac{120{,}221}{110{,}314} = 1.090$	$\left[\frac{1.090}{1.158}\right]^{\frac{1}{10}} = 0.9940$
ETHPOP	110,506	128,000	$\frac{128{,}000}{110{,}506} = 1.158$	

Sources:2001 Census data from table S101; 2011 Census data from table DC2101; ETHPOP data from www.ethpop.org

Dynamic microsimulation

Given an estimated 2011 based population for each LAD and an indication of the future composition of its population in terms of gender, age and ethnicity, the next stage is to evolve this population over the medium term, here to 2031. This is achieved through the following processes:

(i) Age the population by two years. The dynamic microsimulation works in steps of two years (the time interval between ELSA waves).

(ii) Replenish the population at younger ages. As the population ages, the lower age range in each LAD will increase. This necessitates the creation of a population of 'replenishers' at ages 50 and 51 at each time step.

(iii) Update the morbidity status of individuals. This is achieved using hazard models estimated using ELSA data to predict if an individual will develop a morbidity based on their gender, age, ethnicity, smoking status, presence of a co-morbidity, place of residence and time. This probability of occurrence is converted into an actual occurrence using a Monte Carlo approach.

(iv) The structure of the population is adapted to conform to the revised ETHPOP projections for the LAD.

The result of this dynamic microsimulation in terms of the prevalence counts and rates for the English population is shown in Table 23.4. For CVD, the count of those with the morbidity falls by 1 million over the 20-year time period and consequently the prevalence rate halves. This result is driven by changes in lifestyle, occupation and medical advances, e.g. the use of statins to lower cholesterol (Law et al., 2003). The picture for DHBS is the reverse. The count increases by 1.2 million and the rate increases by 2%. The main drivers behind this are poor diet, lack of exercise (which impacts on obesity) and an ageing of the (now) middle aged south Asian population into our 50 year and older age range. With respiratory illness, the count remains largely static over time but because of a larger population at risk, the rate decreases. The reason for this is almost certainly the reduced prevalence of smoking in the population in future years but may also be influenced by changes in occupations. The number with the comorbidity of CVD and DHBS falls by a modest 200,000 and the prevalence rate reduces by half, a consequence of the fall in the prevalence of CVD.

Table 23.4 The numbers and percentages of people aged 50 and older with CVD, DHBS, RI and CVD and DBHS combined, England, 2011 to 2031

The national trends shown in Table 23.4 are simply aggregates of the results for each English LAD. The results for each English LAD in 2031 are shown in Figure 23.2. This figure represents the prevalence counts as circles, with the area of the circle being proportional to the number of people estimated to have the morbidity, whilst the shading indicates the prevalence rate for the LAD. One distinct pattern in the DHBS map is high prevalence rates in LADs located in West Yorkshire, Greater Manchester, the West Midlands and London plus Derby, Nottingham and Leicester. These are all authorities with large BME communities in 2011 and the size of 50 and older population in these communities is projected to increase by 2031.

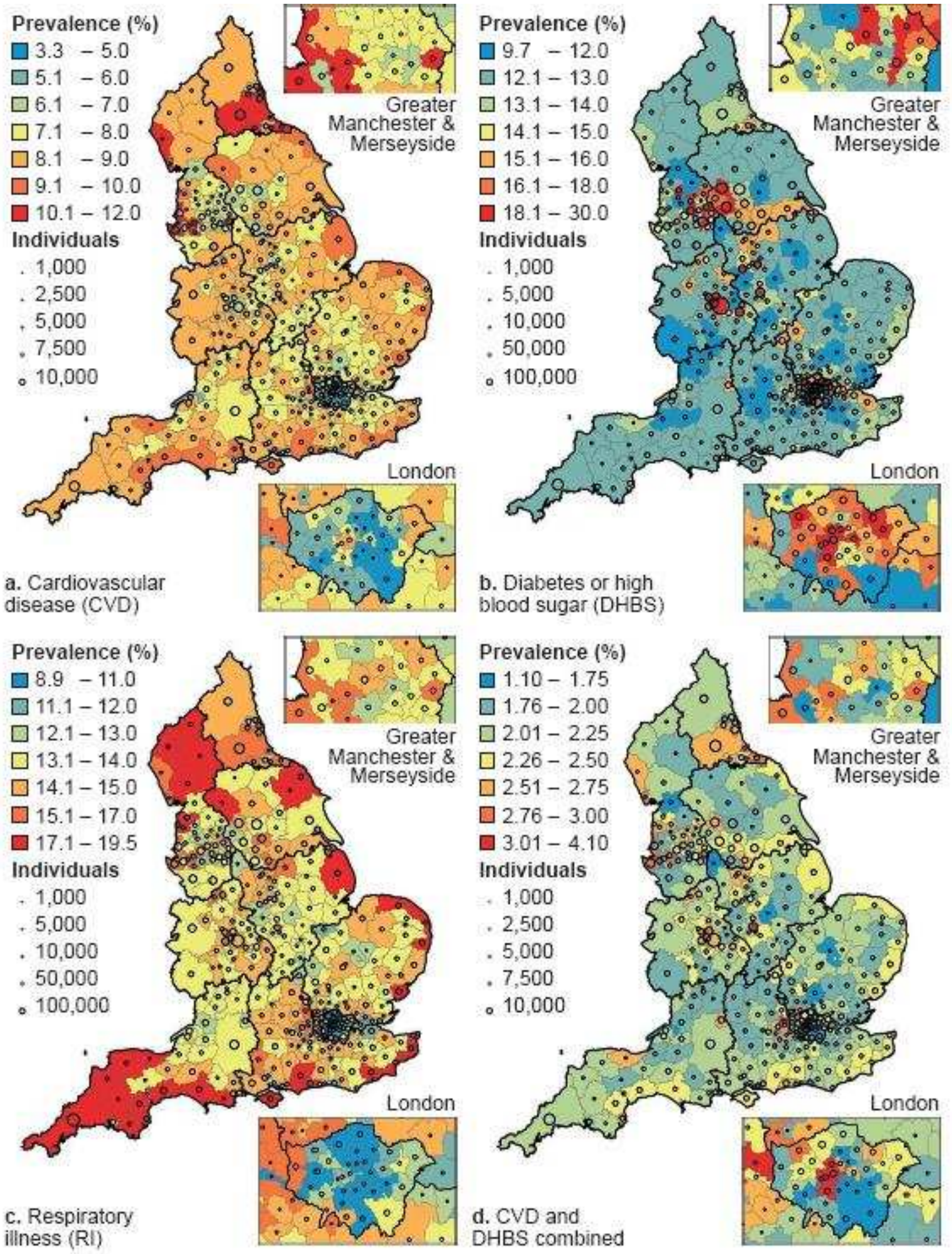

Figure 23.2 Prevalence and number of individuals with morbidities, LADs, England, 2031

23.6 Conclusions

Access to the 2011 Census tabulations has provided a vital component in the dynamic simulation used to project to 2031 the prevalence counts and rates for three important morbidities. The census tables provide a very good estimate of the important covariates associated with these morbidities at a useful geographic scale. However, they are not sufficient. A further data set, the ELSA, is needed to provide additional details on specific health outcomes, in this instance the case study morbidities. The census counts from 2001 and 2011 are also useful to provide a trend in the changing size and composition of the elderly population, particularly in terms of its ethnicity.

Looking at the outcomes of this study, the predicted downward trend in the morbidity for CVD agrees with recent experience (McCulloch, 2012). The hotspots for DHBS prevalence are located in areas where the ethnic composition of the population is such that high prevalence rates would be expected. Changes in smoking behaviour and exposure to toxins in the workplace are stabilising numbers with respiratory illness leading a fall in the prevalence rates.

This framework for analysis and prediction is transferable to other countries that have access to the same types of data, i.e. census or administrative data to provide the detail about the whole population and a sample survey to provide the detail for the domain of interest, such as health.

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Table 23.2 Highest and lowest LADs for prevalence of CVD, DHBS, RI or CVD and RI combined, England, 2011

Rank	Cardiovascular disease (CVD)	%	Diabetes or high blood sugar (DHBS)	%	Respiratory illness (RI)	%	CVD and DHBS combined	%
TEN HIGHEST LADs								
1	Leicester (CI)	18.9	Newham (LC2)	17.3	Leicester (CI)	22.2	Newham (LC)	7.3
2	Tendring (CC)	18.1	Brent (LC2)	17.1	Tower Hamlets (LC)	22.0	Leicester (CI)	7.2
3	Sandwell (CI)	18.0	Leicester (CI)	16.4	Newham (LC2)	21.3	Tower Hamlets (LC)	7.1
4	Tower Hamlets (LC)	18.0	Tower Hamlets (LC)	16.4	Sandwell (CI)	20.9	Brent (LC)	6.6
5	Eastbourne (RC)	18.0	Harrow (LS)	15.6	Wolverhampton (CI)	20.9	Harrow (LS)	6.2
6	Wolverhampton (CI)	17.9	Slough (LS)	15.5	Blackburn with Darwen (CI)	20.8	Hounslow (LS)	6.1
7	Rother (CC)	17.9	Hackney (LC2)	15.5	Knowsley (IH)	20.7	Ealing (LS)	6.1
8	Christchurch (CC)	17.9	Ealing (LS)	15.4	Hounslow (LS)	20.7	Slough (LS)	6.1
9	Thanet (CC)	17.8	Hounslow (LS)	15.3	Birmingham (CI)	20.6	Redbridge (LS)	5.9
10	Wyre (CC)	17.6	Redbridge (LS)	15.2	Slough (LS)	20.6	Manchester (CI)	5.6
TEN LOWEST LADs								
315	South Northamptonshire (PST)	13.6	Elmbridge (PSE)	10.5	Surrey Heath (PSE)	17.1	South Hams (CC)	3.3
316	Daventry (PST)	13.6	Stroud (PST)	10.5	South Northamptonshire (PST)	17.1	South Cambridgeshire (PSE)	3.3
317	Basingstoke and Deane (PSE)	13.5	Bracknell Forest (PSE)	10.5	Waverley (PSE)	17.1	Bracknell Forest (PSE)	3.3
318	Milton Keynes (NGT)	13.4	South Northamptonshire (PST)	10.5	Mid Sussex (PSE)	17.0	Guildford (PSE)	3.3
319	Lambeth (LC2)	13.4	Wokingham (PSE)	10.5	Guildford (PSE)	17.0	South Northamptonshire (PST)	3.3
320	Southwark (LC2)	13.3	Uttlesford (PSE)	10.4	Kensington and Chelsea (LC)	16.9	Basingstoke and Deane (PSE)	3.3
321	Hart (PSE)	13.3	Chiltern (PSE)	10.4	Hart (PSE)	16.9	East Hertfordshire (PSE)	3.2
322	West Berkshire (PSE)	13.2	Mid Sussex (PSE)	10.4	Rutland (PST)	16.8	West Berkshire (PSE)	3.2
323	Wokingham (PSE)	13.2	East Hertfordshire (PSE)	10.4	Tandridge (PSE)	16.8	Surrey Heath (PSE)	3.2
324	Bracknell Forest (PSE)	13.1	West Berkshire (PSE)	10.3	Southwark (LC2)	16.8	Hart (PSE)	3.1

Notes: CI = Centres with Industry; CC = Coastal and Countryside; LC = London Centre; RC = Regional Centres; PST = Prospering Smaller Towns; PSE = Prospering Southern England; NGT = New and Growing Towns; LC2 = London Cosmopolitan; LS = London Suburbs; IH = Industrial Hinterlands
LAD = Local Authority District (the lowest tier of local government in England)

Table 23.4 The numbers and percentages of people aged 50 and older with CVD, DHBS, RI and CVD & DBHS combined, England, 2011 to 2031

Year	Population aged 50 and older	Cardiovascular disease (CVD)		Diabetes or high blood sugar (DHBS)		Respiratory illness (RI)		CVD & DHBS combined	
	Number	Number	%	Number	%	Number	%	Number	%
2011	18,229,893	2,873,694	15.8	2,189,938	12.0	3,408,810	18.7	748,821	4.1
2013	18,964,704	2,803,706	14.8	2,424,851	12.8	3,396,242	17.9	746,541	3.9
2015	19,689,593	2,737,698	13.9	2,656,947	13.5	3,469,615	17.6	751,172	3.8
2017	20,400,332	2,634,641	12.9	2,834,345	13.9	3,495,865	17.1	733,176	3.6
2019	21,083,429	2,531,619	12.0	2,979,780	14.1	3,490,010	16.6	708,491	3.4
2021	21,732,680	2,451,228	11.3	3,128,636	14.4	3,562,378	16.4	696,057	3.2
2023	22,304,919	2,292,377	10.3	3,191,523	14.3	3,477,186	15.6	648,791	2.9
2025	22,755,033	2,207,095	9.7	3,300,025	14.5	3,482,338	15.3	630,625	2.8
2027	23,129,460	2,076,336	9.0	3,358,974	14.5	3,439,145	14.9	592,600	2.6
2029	23,539,913	1,943,832	8.3	3,386,244	14.4	3,366,595	14.3	552,603	2.3
2031	24,029,232	1,858,903	7.7	3,436,486	14.3	3,376,245	14.1	533,763	2.2