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Planning the Location of Stop Smoking Services at the Local Level: A Geographic Analysis

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Smoking is one of the major causes of premature death and its negative effects on a person's health are a global issue. Therefore, the United Kingdom has introduced new policies aimed at reducing the proportion of smokers from 26% in 2005 down to 21% by 2010. One mechanism to meet this policy target is the provision of stop smoking services. This article aims to estimate the Leeds smoking population at the small area level and especially to highlight the distribution of hard-to-reach groups such as heavy smokers (> 20 cigarettes/day) and pregnant women who smoke. Then optimal location strategies are discussed in relation to stop smoking services. The findings show the importance of adding a spatial component to find out where the smoking population or specific subgroups of smokers are to support policymakers or healthcare planners who are responsible for the planning process of the services.

Keywords: estimating smoking rates, stop smoking services, microsimulation, location-allocation models, policy planning

It is estimated that across the world five million people a year die as a result of smoking tobacco products, more than HIV/AIDS, tuberculosis and malaria combined (World Health Organization, 2008). It is generally asserted that around one third of all types of cancers are associated with smoking, with an especially strong link between smoking and lung cancer. Between 1985 and 2002, 1.35 million new lung cancer cases and 1.18 million lung cancer deaths were estimated globally (Parkin, Bray, Ferlay, & Pisani, 2005). Sir Liam Donaldson, currently the Chief Medical Officer for England and the Chief Medical Advisor for the United Kingdom, commented in 2007 that the treatment of smoking-related diseases (including hospital admissions, general practitioner consultations and prescriptions) cost the UK National Health Service approximately £1.7 billion a year. This highlights the importance of supporting individuals to stop smoking and helping to prevent people starting to smoke. Peto, Darby, Deo, Silcocks, Whitley, and Doll (2000) highlight the positive effect on a person's health when he/she quits smoking. For example, the risk of developing lung cancer could be reduced by 90% if people stop smoking before they reach the age of 35.

In England, various interventions have been introduced since 1945 to encourage smokers to quit or refrain from smoking. After initial scientific evidence of the links between smoking and ill health by Doll and Hill (1950), early interventions against smoking were developed by banning the advertising of cigarettes on television. Steps to reduce the smoking population in England also followed with the recommendations of various White Papers by the Department of Health (1998, 2004). The overall aim of the 2004 legislation was to reduce the adult smoking population from 26% in 2005 down to 21% by 2010. To facilitate this, the smoking ban in public places came into effect in July 2007. Further interventions include media and education campaigns, price increases

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for tobacco products, the reduction in tobacco promotion and tobacco product regulation. Another mechanism has been the promotion and proliferation of stop smoking services, first established in England in 1999 to help people to stop smoking. These services are free of charge; people are either referred by a medical person, for instance their general practitioner, or they can 'walk-in' to either attend group sessions or one-to-one sessions led by a trained advisor.

This article discusses the important issue of where stop smoking services should be located given the possibility of targeting different smoking groups. Two models, a spatial microsimulation and a location-allocation model, are applied first to estimate the number of smokers for small geographical areas and second to then locate stop smoking services more effectively. These models are briefly described below. The study area chosen is the city of Leeds located in the north of England with a population size of approximately 750,000. According to estimates by Leeds Primary Care Trust (PCT) the city has a higher smoking rate (around 30%) compared to the national rate (around 24%) (The Healthy Leeds Partnership, 2006). To meet the national target to reduce the proportion of smokers down to 21%, Leeds would need to reduce the smoking population by 9%. This is a hard-to-reach target! Therefore, it is important to consider the local situation in more detail.

For future service provision, and to reduce the number of smokers most effectively, it is necessary to know where and why smoking rates vary, preferably at the smallest geographical level possible, in order to target smokers most efficiently. However, no national datasets related to smoking are accessible for small areas and surveys are expensive and time-consuming. For example, Twigg and Moon (2002) argued that in the mid-1990s a middle-sized health authority would have needed to allocate at least £50,000 to conduct one single survey. This article therefore suggests a methodology for estimating small-area variations in the population that smokes. We shall also explore variations in smoking rates for various population groups of particular concern in policy terms.

Exploring the Number of Smokers for Small Geographical Areas in Leeds

In this section we estimate smoking rates across Leeds using a variety of national datasets to produce local estimates. We begin by looking at one key explanatory variable at a time. We conclude by arguing that we need a methodology to combine these explanatory variables to make more reliable estimates.

Estimated Smokers Based on Age

First, we estimate smoking rates by age. Figure 1 shows the national smoking rates for different age categories for both males and females and it can be seen that the highest rates occur for people in the age group 20 to 24 (31%) whereas the oldest population group (60 and over) have the lowest smoking rate (12%). In all age groups, more men than women smoke, except for the youngest group (age 16 to 19) where the smoking rate is equal between genders (20%).

If the national smoking rates for these age groups are applied to the population of Leeds for output areas then the estimated distribution of smokers is shown in Figure 2. The highest rates can be seen centrally around Headingley, which is also known as the 'student area' of Leeds, the university ward, the northern part of City and Holbeck, Halton to the east of the centre and some areas to the north-east and south of Leeds Centre.

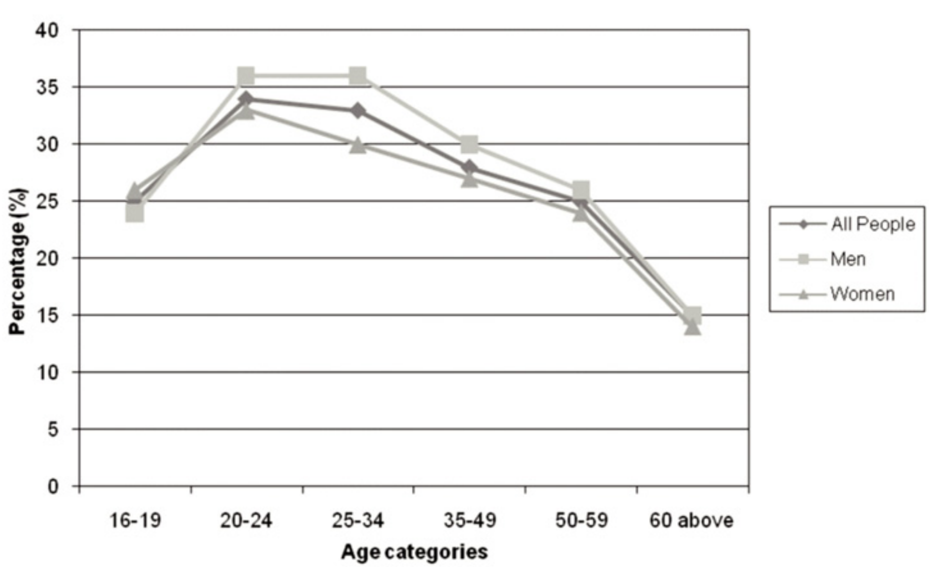

Figure 1

Smoking prevalence (%) by sex and age groups in 2006 (Goddard, 2006).

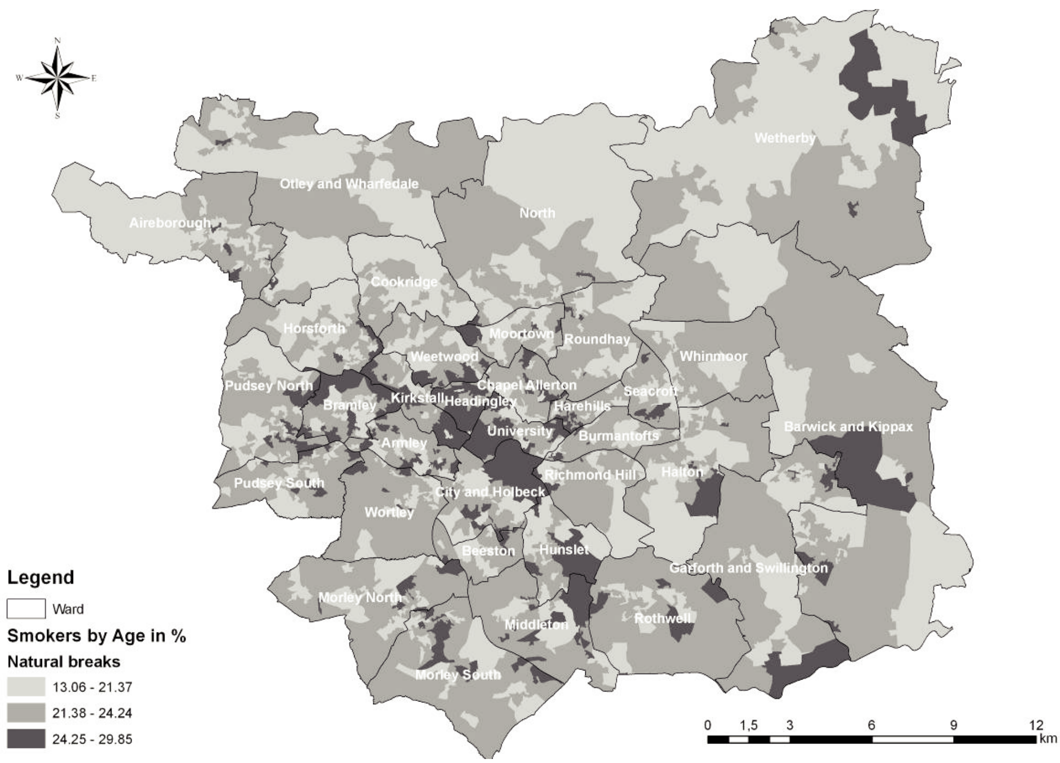

Figure 2

Smoking rates estimated using age group for Leeds output areas in 2006.

Estimated Smokers Based on Socioeconomic Class

The second analysis estimates smoking rates by socioeconomic class. Figure 3 shows the national smoking prevalence rates of the head of household for three socioeconomic categories for the period 2006. It can be clearly seen that there is an increase in the number of smokers moving from higher socioeconomic classes (managerial and professionals) to lower socioeconomic classes (routine and manual workers). Again, there is a higher prevalence among men than women for all three categories.

If these national rates of smoking by socioeconomic class are applied to the population of Leeds, again for output areas, then the estimated distribution of smokers

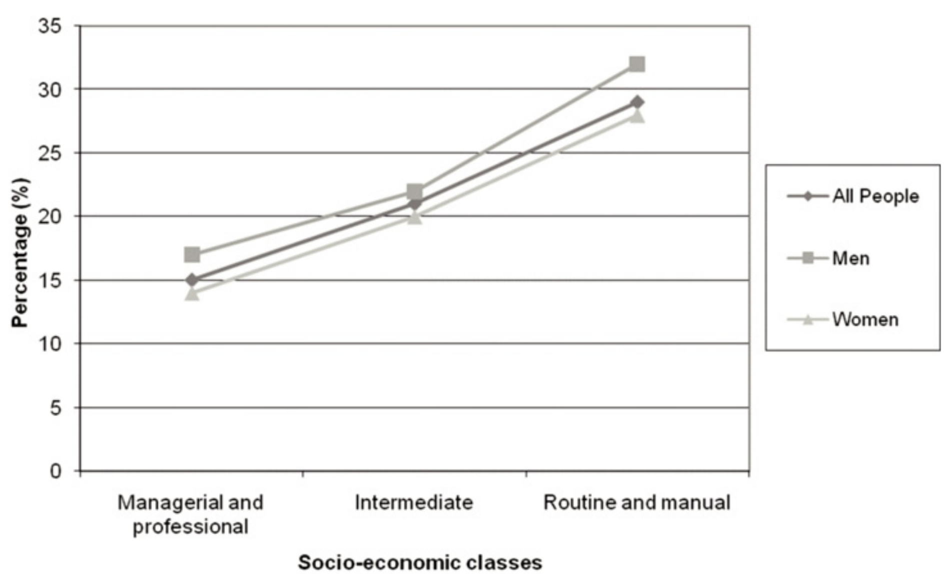

Figure 3

Smoking prevalence (%) by sex and socio-economic class in 2006 (Goddard, 2006).

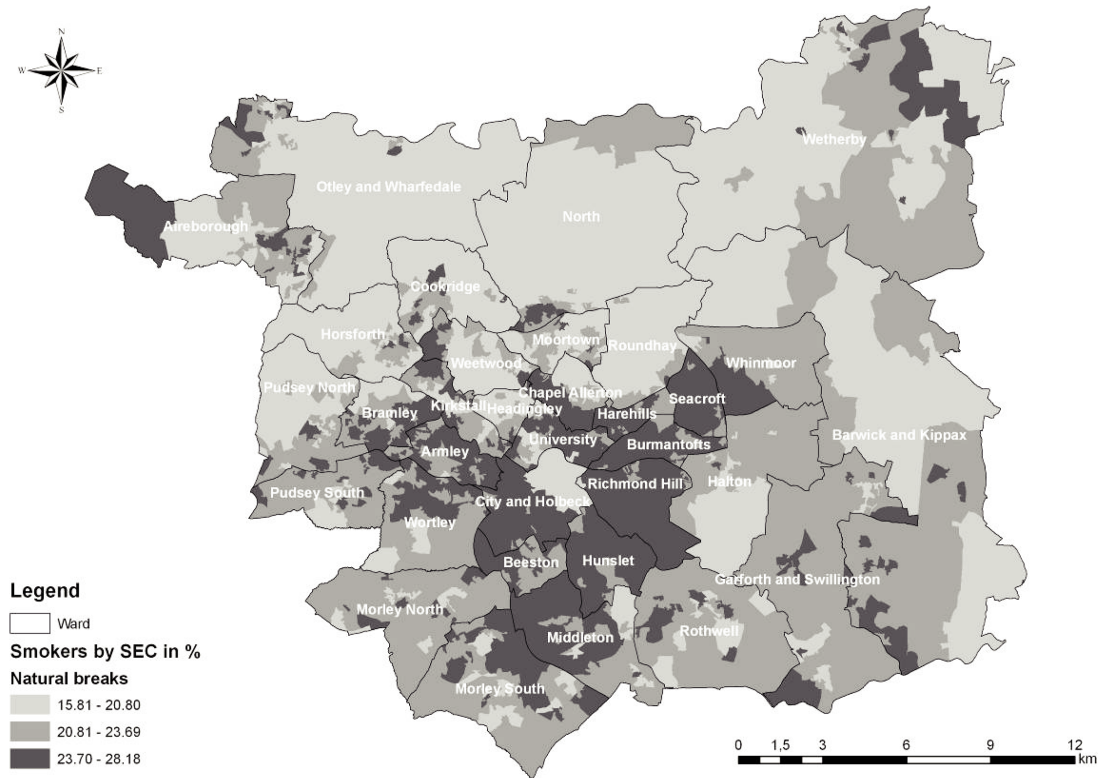

Figure 4
Smoking rates estimated using socio-economic groups for Leeds output areas in 2006.

is as shown in Figure 4. The highest rates are found east of the city centre in Seacroft, Burmantofts and Richmond Hill, south of the city centre (Hunslet and Middleton) and to the south-west of Leeds especially in Morley South. Further, high rates are found to the immediate west of Leeds City Centre including the suburbs of Bramley, Armley and Wortley and to the south (Beeston). Finally, we can see high rates in central Leeds including parts of City and Holbeck, Harehills and University. Most of these areas are known to be deprived areas. Lowest rates can be found in the northern parts of Leeds, the more affluent areas.

It is interesting that social class appears most often in the literature to explain variations in smoking rates (Hart, Hole, Gillis, Davey Smith, Watt, & Hawthorne, 2001). Indeed, when looking at the incidence of smoking-related illnesses in Leeds there is a high correlation with social class. Figure 5 below, for example, shows the distribution of lung cancer deaths in Leeds. The data for lung cancer mortality cases were obtained from the Office of National Statistics for the area of Leeds at output area level. Data for the year 2001 and 2002 were combined together to get a total of 1,023 cases. PCT guidelines prohibit showing data for areas with less than 5 counts (due to confidentiality constraints). Thus, it was necessary to aggregate the data to ward level (there are 33 wards in Leeds) in order to calculate lung cancer mortality rates using 2001 census population data. Figure 5 shows that the highest lung cancer mortality rates occur in Hunslet, City and Holbeck and Burmantofts (most deprived wards) whereas lowest rates occur in North, Wetherby, Moortown, Halton, Rothwell, Morley North and Morley South (less deprived wards). When comparing Figure 5 and Figure 4, it can be clearly seen that there are common geographical patterns between areas with high lung cancer mortality rates and areas with high rates of smokers when estimated by socioeconomic class. Thus, if only one variable had to be chosen, perhaps social class would be the most useful.

Estimated Smokers Based on Ethnicity

The third analysis presents the smoking prevalence rates by ethnic groups for the period 2001 until 2005 (Figure 6). The data were combined over the years to get a reliable sample size. The Mixed population (White and Black Caribbean, White and Black African, White and Asian, Other Mixed) have the highest smoking rates followed by the White population (White British, White Irish, Other White). For all groups, men are more likely to smoke than women. Interestingly, a huge gap can be seen for the Asian and Asian British and the Chinese and Other ethnic groups where women have very low smoking rates in comparison to men.

If these national rates of smoking by ethnicity are applied again to the population of Leeds for output areas

Figure 5

Lung cancer mortality rates (%) in Leeds: 2001 to 2002.

then the estimated distribution of smokers is shown in Figure 7. It can be seen that highest smoking rates are outside the centre of Leeds and that there are no great variations in smoking rates across output areas. This is due to the high numbers of White people living in Leeds in comparison to the other ethnic groups. To demonstrate this, Figure 8 shows the smoking rates for the male Asian or Asian British population only, and it can be seen that the highest smoking rates appear in the centre of Leeds, namely Harehills and Chapel Allerton, where a relatively high proportion of Asian people live. This pattern was not evident beforehand because the Asian

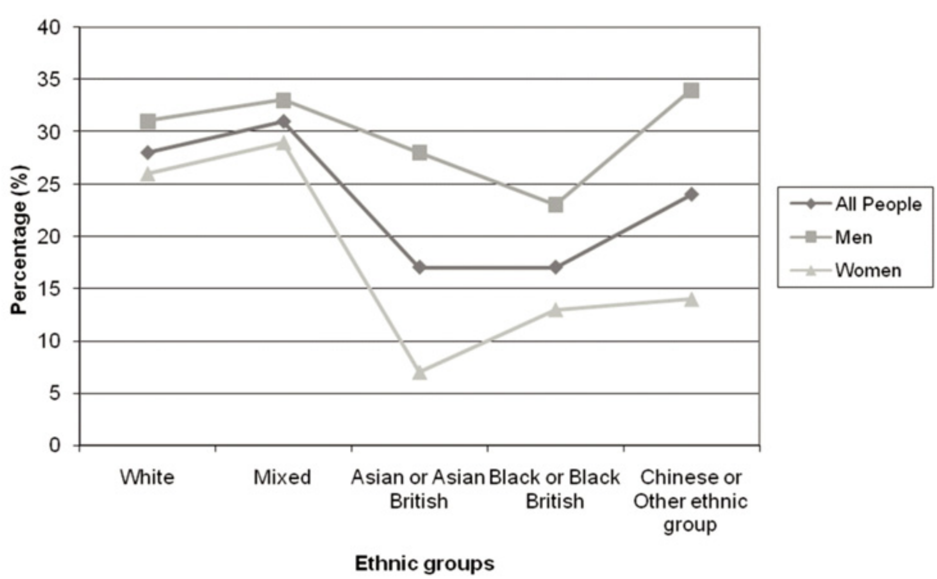

Figure 6

Smoking prevalence (%) by sex and ethnic groups: 2001 to 2005 (Goddard, 2005).

Figure 7

Smoking rates estimated using ethnic groups for Leeds output areas: 2001 to 2005.

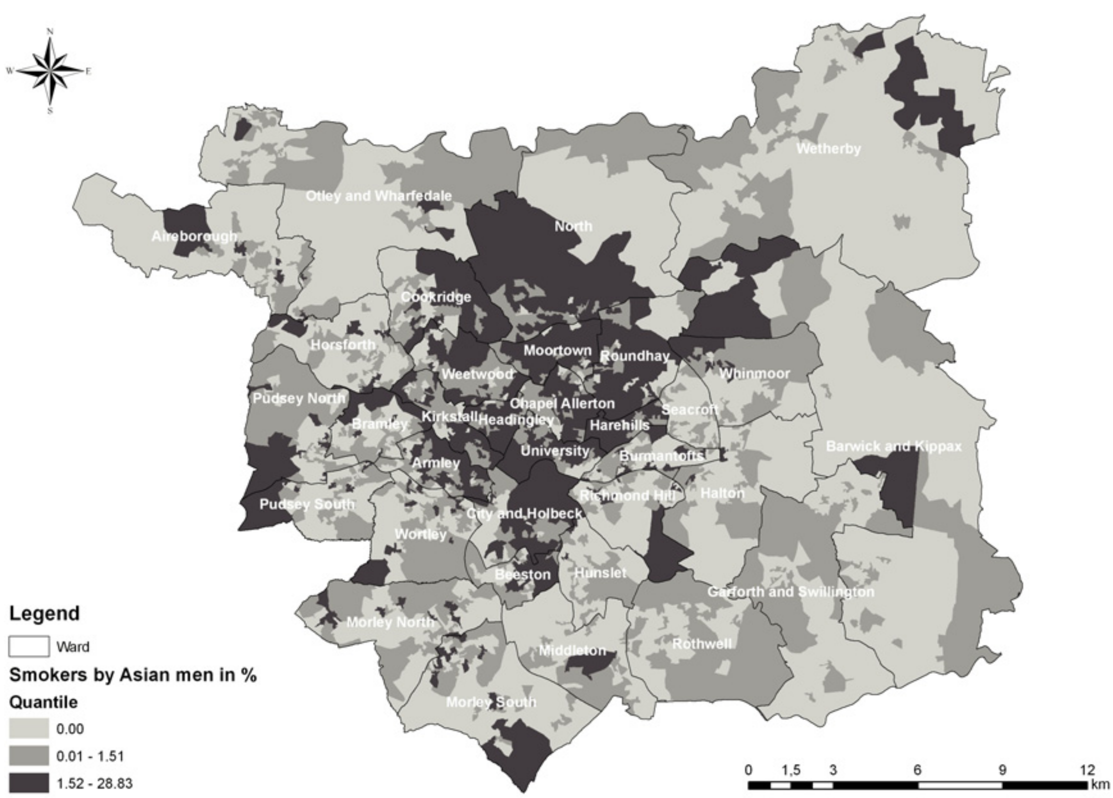

Figure 8

Smoking rates estimated using the Asian male population for Leeds output areas: 2001 to 2005.

and Asian British women have the lowest smoking rates in comparison to the other ethnic groups, and thus the average overall masked the high male rates.

Summary

The smoking estimations produced above provide a guide to areas with high and low smoking prevalence. However, different variables show different areas of high and low smoking prevalence that makes planning the locations of stop smoking services more difficult. For instance, when targeting a reduction in smoking based on smoking prevalence by age then more stop smoking services would be needed in the north-west, inner areas of Leeds. If socioeconomic status is used then more services would be needed in the eastern suburbs of Leeds, namely Seacroft, Burmantofts and Richmond Hill. To target the male Asian community then facilities would be needed in the inner northern suburbs of Harehills and Chapel Allerton. To help overcome this problem we have developed a spatial microsimulation method to combine these variables in such a way as to produce one best final output. This is explored in more detail in the next section.

Estimating More Reliable Smoking Rates

It was argued above that it would be useful to combine estimates of smoking based on age, sex, social class and ethnicity. The methodology we adopt here to do this is spatial microsimulation. Although there are various types of microsimulation models, and various ways of building such a model (see Ballas, Rossiter, Thomas, Clarke, & Dorling 2005; Ballas, Clarke, Dorling, & Rossiter, 2007; Tomintz, Clarke & Rigby, 2008) we shall only describe the methodology adopted for this study. Microsimulation is a technique that allows us to reweight survey data so that we can take each household in the city and match it to a household in that survey. This is a technique known as deterministic reweighting (Ballas, Rossiter, Thomas, Clarke & Dorling, 2005). To do so, two datasets (the General Household Survey [GHS] 2006 and the United Kingdom [UK] census 2001) are integrated. The GHS is a national cross-sectional survey that is conducted annually. The large dataset holds information of individuals or households but has no indictor of local address (to protect confidentiality). There are, however, a number of smoking-related questions asked in the survey relevant to this study. The UK census 2001 provides information down to census output level for many demographic and socioeconomic variables (but of course no information on smoking is given). Thus the datasets can be effectively combined by searching for similarities across socioeconomic variables and assigning a smoking/non-smoking estimate for each household in the city, based

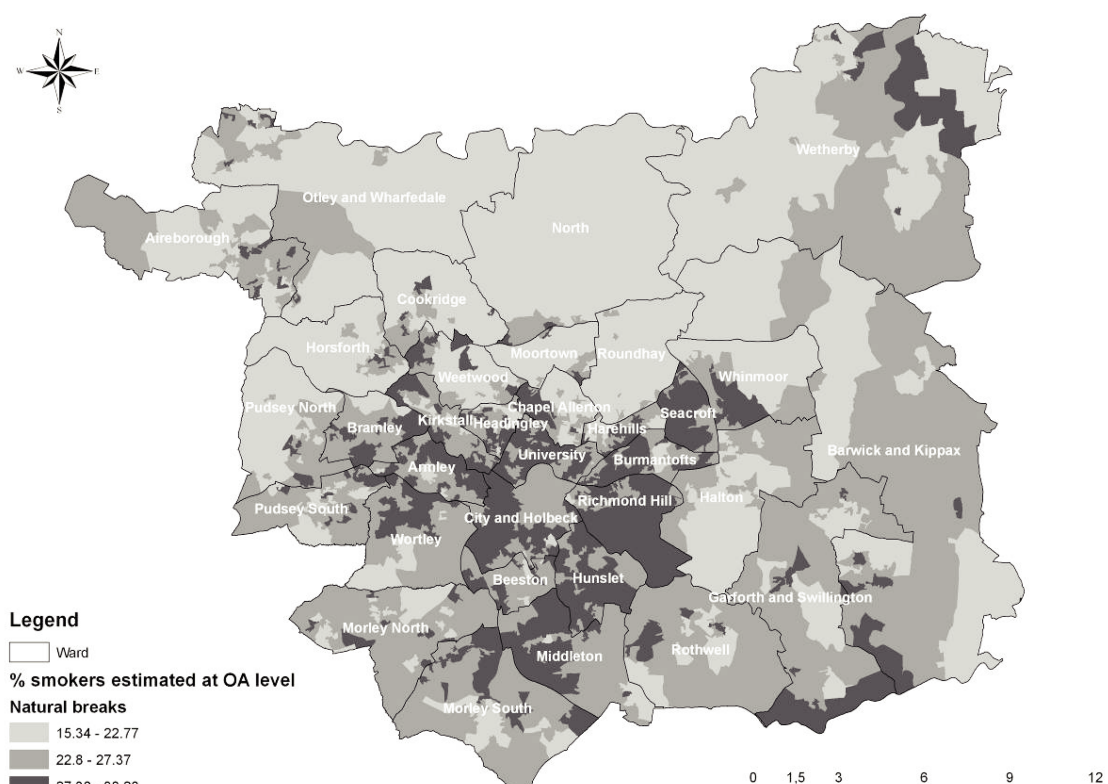

Figure 9

Estimated smoking rates for Leeds output areas from the spatial microsimulation model.

on its age profile, socioeconomic status and ethnicity. For example, a young unemployed Chinese male is very likely to be assigned to the category 'smoker' given that the survey tells us smoking is higher in younger age groups, more deprived groups and among certain ethnic groups (such as Chinese). Figure 9 shows the estimate of smoking rates in Leeds using this methodology.

The result can be seen to be a combination of the results shown in Figures 2, 4 and 7, and would seem to be a more accurate reflection of likely smoking rates across the city.

As the GHS also gives more detail on number of cigarettes smoked by different socioeconomic groups it is also possible to use this methodology to estimate the distribution of specific groups that health authorities may wish to target. Two groups we have identified in this respect are first, heavy smokers, and second, pregnant females (although others could be easily targeted too). A key policy target in England (which is also applied to Leeds) is to reduce the number of heavy smokers, or at least reduce the number of cigarettes they smoke. The GHS 2006 asks how many cigarettes a person smokes on average per day. This information is used to estimate four categories of smokers: (1) *never smoked or ex smoker* (77.6%), (2) smokes 1 to 9 cigarettes/day = *light smokers* (6.4%), (3) smokes 10 to 19 cigarettes/day = *moderate smokers* (9.6%), (4) smokes 20 or more cigarettes/day = *heavy smokers* (6.5%). The results of the simulation are shown again for the 2,439 output areas in Leeds (Figure 10). The smoking prevalence for this target group is estimated to vary between 3.09% and 9.38%. As can be seen, the highest rates are found in the most deprived areas of Leeds (Seacroft, Burmantofts, Richmond Hill, Hunslet, Middleton, Beeston, Bramley). This shows the strong association between heavy smoking and social status. Heavy smokers in more deprived areas need to be targeted not only for health reasons: they often have less income and spend a lot of money on cigarettes (which could lead to less expenditure on more healthy food). Heavy smokers also have greater difficulties in stopping smoking as they are often more addicted to the nicotine in cigarettes. In theory, therefore, it could be harder to convince them to attend available stop smoking services and quit smoking (or at least reduce the amount of cigarettes they are smoking) if these services are not provided very locally (i.e., made very accessible).

High also on the UK policy agenda is to target pregnant women who are likely to continue to smoke during their pregnancies. Delpisheh, Kelly, Rizwan and Brabin (2006) used questionnaires to show that a third of mothers smoked during pregnancy, with a high proportion among women in disadvantaged population groups. They also showed that mothers that smoke are at significant risk of experiencing an adverse birth outcome (such as low birth weight and a preterm birth). Problems arise from the fact that premature babies are not fully devel-

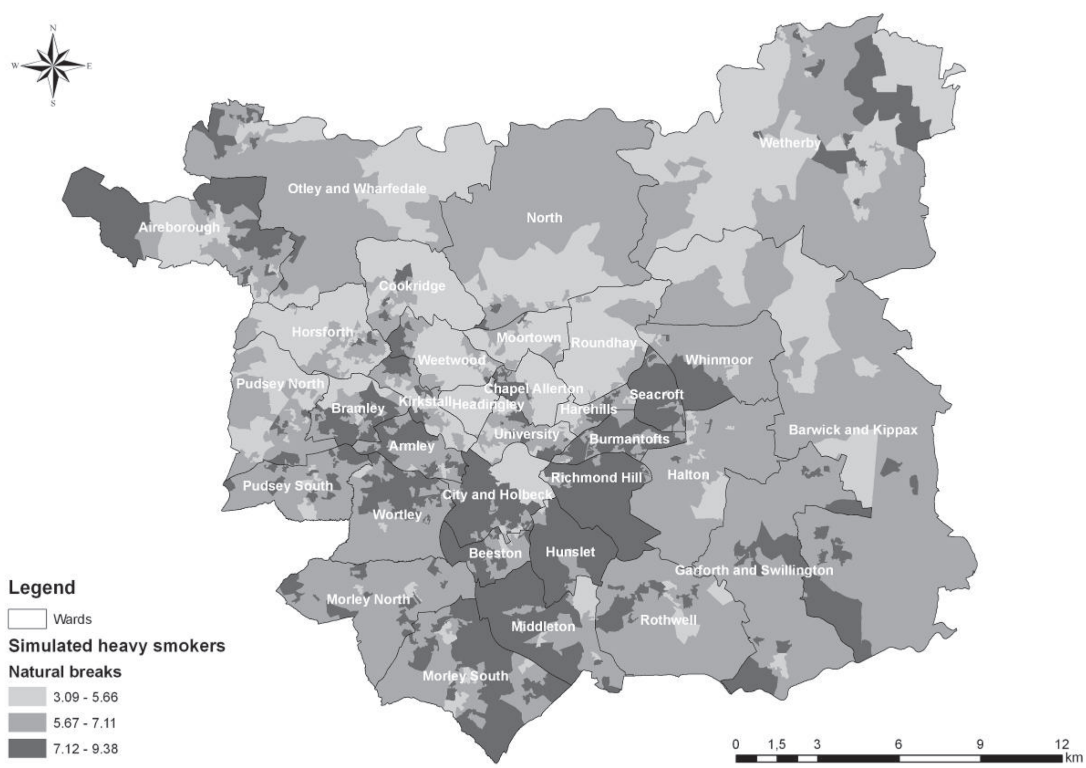

Figure 10

Simulated smoking estimates (%) for *heavy* (20 or more cigarettes/day) smokers in Leeds.

Figure 11
Number of women who are likely to smoke during pregnancy.

oped and therefore they can have difficulties with feeding and breathing. They also found that pregnant women who smoke are at higher risk of miscarriages and perinatal deaths and that smoking can harm the development of the foetus and the newborn child. The possible negative health outcomes for a baby occur not only when a mother smokes but also when she is exposed to passive smoke. Passive smoking also influences birth weight and length of gestation (Stanton, Martin, & Henningfield, 2005). Further, Lam, Leung and Ho (2001) found that there is an increased health risk for children in their first 18 months of life when non-smoking mothers are passive smokers. Hamisu, Salihu and Wilson (2007) supported the findings that despite a decline in maternal smoking there is still evidence that it accounts for a significant proportion of foetal morbidity and mortality. In general, younger mothers are more likely to smoke and a key concern is that it has been estimated that around 36% of pregnant women in Leeds smoke (which is much higher than the estimated national rate of 23%; The Healthy Leeds Partnership, 2006, p. 6). So age is again important here.

The spatial microsimulation model was used to estimate the number of smokers who are currently pregnant or have been pregnant in the last 12 months. This was done by combining the UK census 2001 with another survey data set — the Health Survey for England (HSE) 2006. Figure 11 shows the estimated number of pregnant women who have smoked during pregnancy (this was modelled for output areas and aggregated to ward level for visualisation purposes). It can be seen that highest numbers are in Wetherby, Harehills, Rothwell and Morley South. These areas do not have the highest smoking prevalence in general, but it seems there are a high number of pregnant women likely to smoke in these areas. Further, higher numbers can be seen in more deprived areas including Burmantofts, Richmond Hill, Hunslet and City and Holbeck.

Locating Stop Smoking Services in an Optimal Fashion

Location-allocation models are a useful planning tool, especially for the location of public sector services. There are a number of useful illustrations in the literature (Coombes & Raybould, 2004; Hodgson, 1988; Ross, Rosenberg, & Pross, 1994). The models work by locating services in such a way as to minimise the distance or time taken to reach the services, taking into account the uneven distribution of demand for that service (for the entire population in a city or region). Rather than using straight-line distance a road network can be added to the model to reflect travel times more accurately (downloadable from EDINA web site: http://edina.ac.uk).

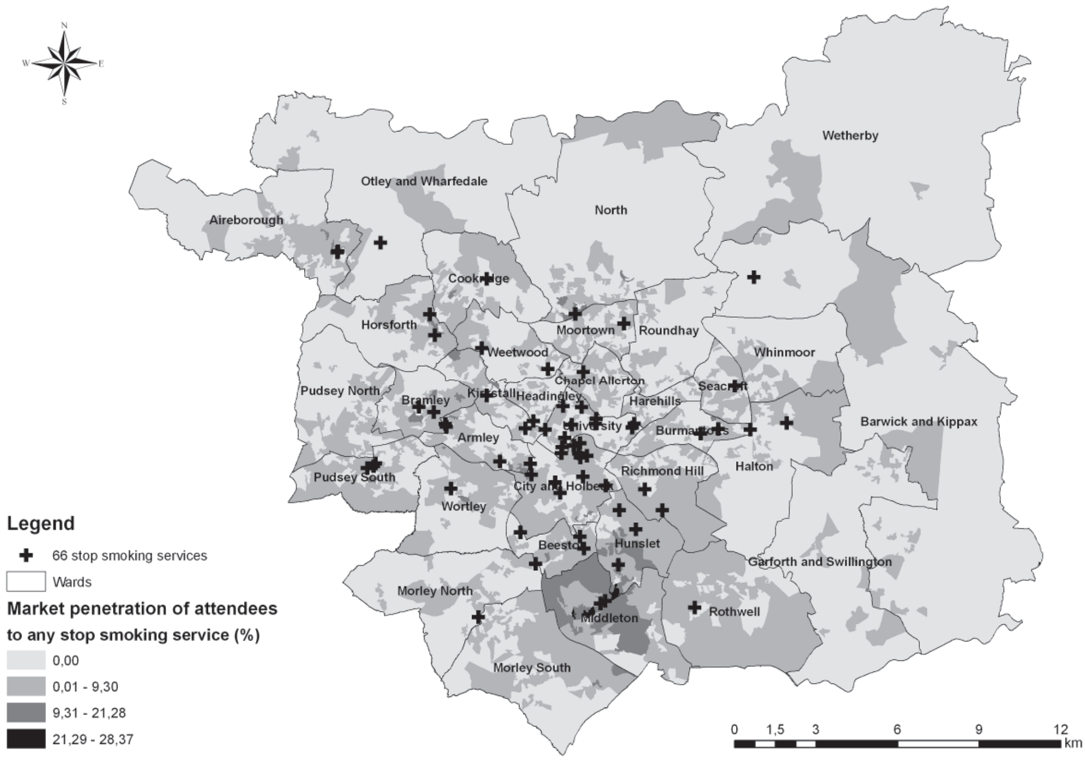

Figure 12

Market penetration of smokers attending any stop smoking service in 2006/2007 at output area level based on simulated smokers.

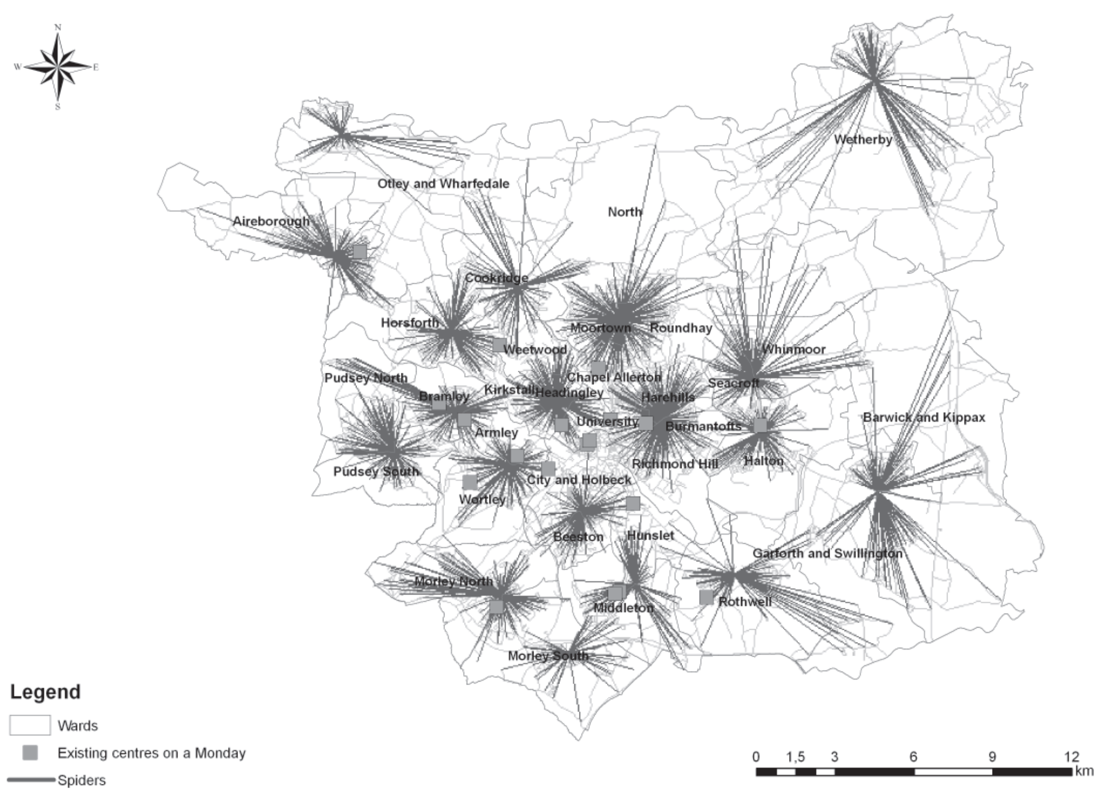

Figure 13

19 current versus 19 'optimal' locations for stop smoking services based on the number of heavy smokers by using a location-allocation model.

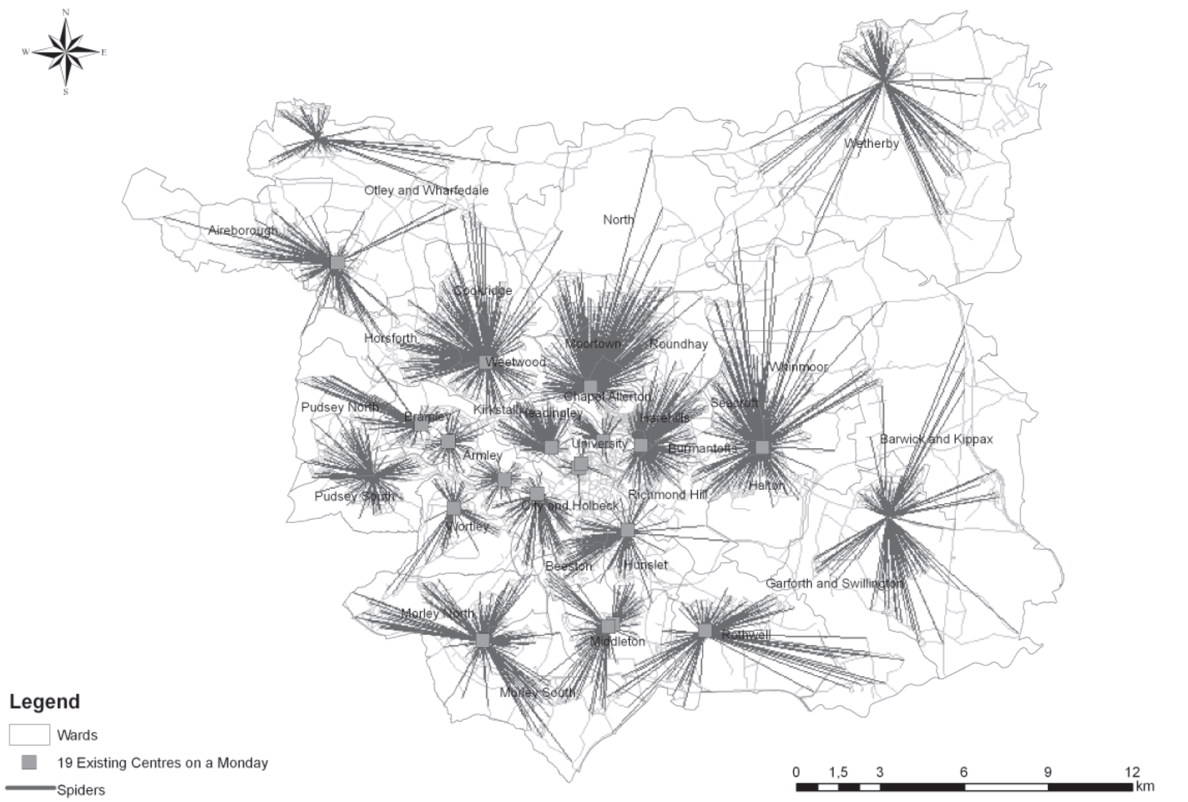

Figure 14

'Optimal' locations for four additional stop smoking services based on the number of simulated heavy smokers.

In addition to finding optimal sites for future provision it is useful to evaluate the distribution of current locations used in Leeds. Information about stop smoking services in Leeds was provided by the Leeds PCT so it was possible to know how many services were in daily operation, the location of the services, the time and day a service was running as well as the utilisation of each service. Leeds PCT has chosen a policy of varying the location of centres on a quarterly basis. Between 2006 and 2007 (last data collected by the time of this research) 66 locations have been used with typically 9–10 operational on a single day. This approach is useful in that services are effectively more mobile, but fixed locations in the best areas might be preferable in terms of accessibility to most smokers and providing greater, more permanent support for those that use such services. For example, Figure 12 shows the widespread variations in success rates across Leeds achieved to date using this strategy, measured as the percentage of the estimated number of smokers who have visited a stop smoking service. There are areas of Leeds where the market penetration of the stop smoking services is extremely low.

In addition, it is possible to run the location-allocation model for the disaggregated demand sets of (a) heavy smokers and (b) pregnant women. Figure 13 shows the outcome of running a location-allocation model for 19 centres in Leeds, 19 being the most provided regularly on a single day. The location model uses the estimated distribution of heavy smokers from the microsimulation model as the demand variable. The result shows the current and the proposed optimal locations for 19 stop smoking services with the aim of minimising the travel distance for smokers who smoke twenty or more cigarettes a day. It can be seen that few current locations match the optimal locations. Further, it is shown that the optimal location analysis would require services to be set up in more suburban areas such as Otley and Wharfedale in north-west Leeds, Wetherby in north-east Leeds, Barwick and Kippax in east Leeds and Garforth and Swillington in the south-east of Leeds. New centres would also be useful in Morley South, which is located in south Leeds, between Pudsey North and Pudsey South in West Leeds, Horsforth and Cookridge located in north-east Leeds, and Moortown in the north of Leeds. These changes would provide more equal access for heavy smokers by reducing the average travel distance down to 1.9 km and the furthest distance travelled to 8.7 km. These figures are compared with the existing service points where the average distance travelled is 3.1 km and the furthest distance travelled is 18.8 km. Such relocations could increase the attendance rate of smokers, although other factors including good advertising and good cooperation with pharmacies, dentists and GPs

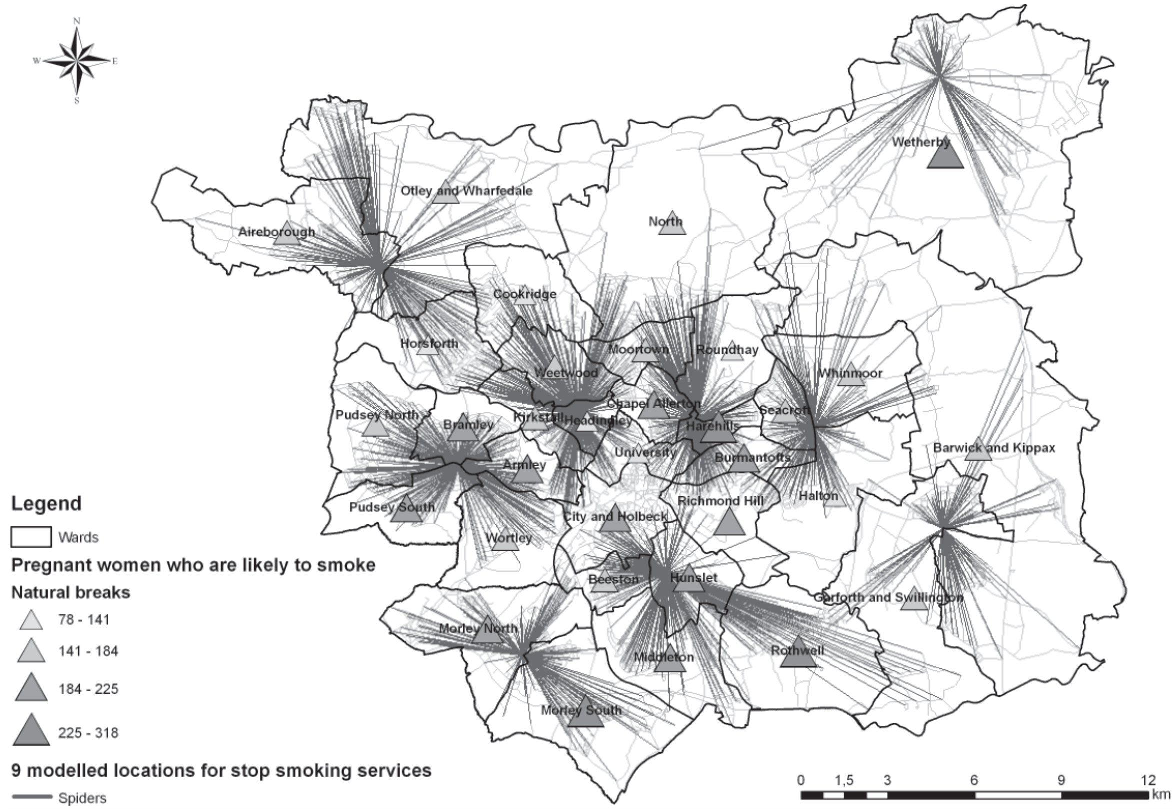

Figure 15

Estimated numbers of women who are likely to have smoked during pregnancy aggregated to ward level in combination with 9 'optimal' locations for stop smoking services that were modelled based on the estimated smoking population.

(who can transfer smokers to stop smoking services) are crucial to make smokers aware of these services and to encourage their use.

The next scenario shows a different use of the location-allocation model. Here, the aim is to find optimal locations for four additional stop smoking services (where the number of additional services is chosen randomly for demonstration purposes) if additional money were to become available. The 19 most frequently offered services are used (as in Figure 13) as a base. This might be a more realistic scenario for change if the 19 existing locations are effectively difficult to move (perhaps if they are associated with existing health clinics or GP surgeries). The results are shown in Figure 14 where the grey squares on the map represent the existing stop smoking services and the grey lines show the areas that the stop smoking services cover. The remaining four 'spiders' without grey squares are best additional locations for stop smoking services to target heavy smokers most effectively. The model proposes to locate these additional stop smoking services in the north-west, west, north-east and east of Leeds. This shows the demand from heavy smoker residents in these areas. When adding four additional services then the average distance a smoker would need to travel is 2.2 km whereas the furthest distance would be 9.4 km.

A final scenario was to find the optimal locations of centres to serve pregnant women who smoke. To show the flexibility of the approach we use only nine centres this time, this being the average available number of services a day during the 12-month period of data collection. With such information, best locations for stop smoking services to target pregnant women who smoke can be identified. The result in Figure 15 shows that the numbers of pregnant women who are likely to smoke vary between 78 and 318 for wards. It can be seen that a stop smoking service in Wetherby would be useful, as well as the stop smoking service added in Harehills. High demand for a service can also be seen in Rothwell in the east, Morley South and Richmond Hill where no stop smoking service is currently located.

Conclusions

This article highlights the importance of a detailed local approach to estimating smoking rates. Although national and regional smoking rates are available and can be used to derive estimates of the geography of smoking in a region based on rates for different age groups, social class and ethnic groups it was shown that the patterns of high and low smoking rates can vary markedly when using only one variable. This makes it more difficult for healthcare planners to target the smoking population in its entirety. To overcome this problem, spatial microsimulation was used to combine these different variables to produce a single, more reliable estimate. Further, the advantage of spatial microsimulation was shown in terms of the ability to modify the output variable from the initial smoker/non-smoker to different categories, such heavy smokers or pregnant women who smoke. We believe the findings of this article can make a valuable contribution to health-care planners who are responsible for locating stop smoking services efficiently. Although the results remain estimates only, we believe it is a powerful methodology for combining the most important variables for explaining small-area variations in smoking rates. More discussion on model validation appears elsewhere (Tomintz, Clarke & Rigby, 2008). When location-allocation models are added then it is possible to match service locations to the estimated population of smokers far more effectively.

Future research may be carried out in a number of areas. First, although the addition of a detailed road network implemented here is an improvement over straight-line approaches, access to public transport would be a useful additional factor to incorporate. This could improve the model as people from disadvantaged areas are more likely to be dependent on public transport. Second, we have only considered home to service flows here. In reality, persons may be closer to a centre through their place of work. A more complex model could evaluate the daytime population as opposed to purely the residential or census-based population totals. These remain interesting avenues of research to address in the future.

Acknowledgments

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