Dr Who? An Analysis of GP Utilisation across Galway City and County

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Abstract

This paper analyses the effect accessibility has on General Practitioner (GP) utilisation rates at the sub-national level for Ireland. Specifically, the aim of this paper is to estimate whether there is an urban/rural differential in GP utilisation rates. We do this by simulating micro-level health care data. Using this synthetic data, simple logit models are employed to estimate the likelihood that individuals in different localities will attend a GP surgery. These individual logit estimates are then inputted into a spatial interaction model to highlight areas with low GP accessibility given their health status. The policy implications of these results are discussed in relation to both the health care literature and current Irish health care policy.

Key words: Accessibility, Spatial Interaction Models, Spatial Microsimulation, Rural Health Care

1. Introduction

While health is a property of the individual, data and computational limitations have meant that most research into health inequalities across space has been analysed at the aggregated regional or country level. Recent research has pointed out that factors that explain variation in health status at one spatial scale may be quite unimportant at another (Gatrell, 2002). For example, international variations in health status may be a function of government expenditure on health care, while variation within a country may be due to environmental factors.

From a methodological aspect, the use of aggregated spatial scales may also impact on one's results. Rural areas generally have a larger geographical area and much smaller populations compared to their urban counterparts. As the number of individuals commuting increases rural areas also tend to be more socially heterogeneous than urban areas, with a greater mixture of rich and poor living side-by-side (Meredith, 2006). Given the heterogeneous nature of rural areas, aggregate measures of health status are likely to be non-representative (Cox, 1998) and unreliable (Phillimore and Reading, 1992).

Given this background, the main objective of this paper is to estimate the spatial distribution of GP visits across both rural and urban areas at the Electoral District (ED) level in county Galway, Ireland. The principal reason that Galway was chosen as the area of interest for this analysis, is that while Galway is a predominately rural county, it is also home to one of Ireland's top five urban concentrations. We believe that the use of simulated micro-level data will present a different spatial picture of health service demand than previous research has shown and that rural rather than urban areas might actually have higher health service demand.

The remainder of this paper is structured as follows. Section 2 gives an overview of the spatial microsimulation process and the data used in the analysis. Section 3 then discusses how we model an individual's *propensity* to visit a GP using a logit specification. The use of spatial interaction models in order to allocate patients to a GP surgery is discussed in section 4. The outputs from these models are then presented in section 5. Finally, concluding comments in terms of policy recommendations are presented in section 6.

2. Data Sources and the Creation of Spatially Disaggregated Microdata

The first step in our modelling framework is to create a spatially disaggregated micro dataset, which contains the necessary variables to estimate GP utilisation patterns. Although there are a number of datasets containing spatial identifiers for each individual in the dataset, these tend to be at a very aggregate level. The Living in Ireland (LII) dataset for example contains a spatial variable broken down by only 12 possible categories: the five cities in Ireland, a category for

Dublin County, an ‘open-countryside’ category, and five categories for towns of varying sizes. The LII survey is the Irish component of the European Community Household Panel (ECHP) dataset. The LII survey was a seven year longitudinal survey that began in 1994 and ended in 2001. The sampling frame used for the LII is the Irish Register of Electors. The LII dataset for 2000 contained 13,067 individuals. In addition to information on a variety of individual, demographic and socio-economic characteristics, the LII also contains detailed information on individual health status (both physical and mental) and health service utilisation rates in the previous year (GP, optician and dentist as well as the number of nights spent in hospital).

On the other hand, the Irish Small Area Population Statistics (SAPS) contains a rich set of census information at the small area level – in this case for electoral divisions (EDs). EDs are the smallest geographical output area for Ireland. There are 238 EDs in Co Galway. The population in any one ED ranges from a low of 96 individuals to a high of 11,238, with an average across all EDs of 885. However, as with most censuses, the data available on individual’s health status is limited. If we could merge the data in the LLI with the ED Census level data we would have a much richer dataset that would allow us to investigate GP utilisation at a very local level of spatial resolution. We use spatial microsimulation techniques to accomplish this.

SMILE (Simulation model of the Irish Local Economy) is a static spatial microsimulation model (Hynes et al., forthcoming). Using a combinational optimisation technique, simulated annealing, to match the LII (2000) to the SAPS (2002), SMILE produces a micro-level synthetic dataset for the whole population (4 million individuals) of Ireland (for a full discussion on the datasets and algorithm used to create the statistical match, please see Morrissey et al., forthcoming). The dataset created by SMILE contains the usual demographic, socio-economic, labour force and income variables for both individuals and family units. However, unlike other microsimulation models SMILE also contains a farm (Hynes et al., forthcoming) and health component (Morrissey et al., 2008).

The synthetic dataset created by SMILE contains approximately 150 variables, representing a complete demographic, socio-economic and health profile for each individual in Ireland. SMILE's main demographic, socio-economic and health variables, their data source and their status (match or unmatched variables) are listed in Table 1. As one can see, the majority of variables contained in Table 1 are not used in the matching process. Thus, before these variables may be used for policy analysis, their validity must be tested.

Table 1: The main Demographic, Socio-economic and Health variables in SMILE

	LII	Census	Status
Age	Yes	Cross-tabulated with Sex	Matched Variable
Sex	Yes	Cross-tabulated with Age	Matched Variable
Martial Status	Yes	Yes	Non-Matched Variable
Household Size	Yes	Yes	Matched Variable
Number of Children	Yes	Yes	Non-Matched Variable
Household Income	Yes	No	Non-Matched Variable
Education Level	Yes	Yes	Matched Variable
Employment Status	Yes	Yes	Non-Matched Variable
Farm Owner	Yes	Yes	Non-Matched Variable
Health Status (5 category dummy variable)	Yes	No	Non-Matched Variable
Long Term Illness	Yes	No	Non-Matched Variable
GP utilisation	Yes	No	Non-Matched Variable
In-patient Utilisation	Yes	No	Non-Matched Variable
Nights spent as an in-patient	Yes	No	Non-Matched Variable
Smoker or not	Yes	No	Non-Matched Variable

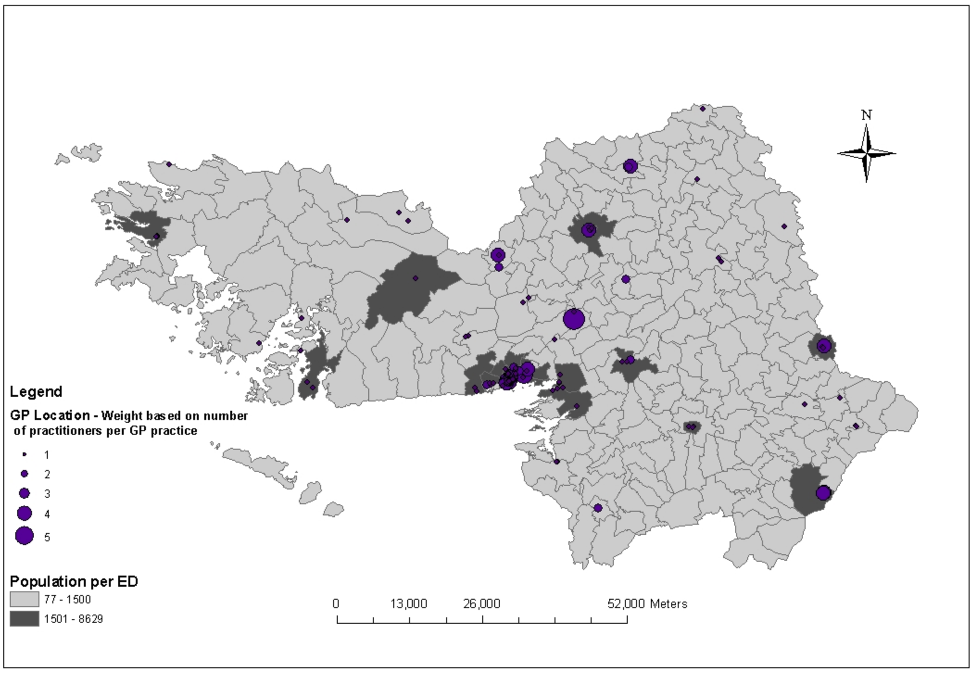
As mentioned above, spatial microsimulation is a method used to create spatially disaggregated microdata that previously did not exist. Thus, validation of the newly created data is essential. SMILE contains a number of internal validation methods, namely z-scores, z^2-scores and total absolute measure scores (Hynes et al., forthcoming). However, a serious weakness of internal validation is that it fails to compare the fitted model with 'fresh' external data. External validation arises when the newly created variables in SMILE are compared to similar data that is not used in the original match. With regard to our data, the simulated GP utilisation variable is validated against the 2001, special health module of the Quarterly National Household Survey (QNHS). The QNHS is a representative dataset for the whole of Ireland. Producing variables at the NUTSIII and county spatial levels, it was found that the rates of GP utilisation were similar between the SMILE dataset and the QNHS. SMILE predicted 76% of Galway's population used a GP service in 2002, while the QNHS reported that 78% of Galway's population used a GP. As Ballas et al. (2001) point out, model validation is an essential component to the spatial microsimulation methodology and it is only through validation that the integrity of the model is established.

3. Estimating demand for GP services using Logit Modelling

There is considerable research on the individual attributes that affect the decision to utilise a GP surgery in Ireland (Madden, Nolan & Nolan, 2005). Using the simulated data from SMILE (net individual income, educational attainment, age, gender, the presence of an illness, eligibility for free public health care (known as a medical cardholder), marital status and private car ownership), a simple logit model was used for each ED to estimate which areas in county Galway (given the demographic and socio-economic characteristics of the residents), are most likely to have high demand for GP services.

Although, we could use the simulated ('real') demand for GP services to look at patterns of GP attendance, this paper is interested in both revealed (has used a GP service) and potential (may need to use a service, but has not) demand. Therefore, the logit model for each ED is used to estimate potential demand for GP services given each individual's characteristics. This in turn gives us a broader picture of demand for GP services rather than revealed demand alone. Figure 1 maps the spatial distribution of actual GP services in Galway, by size (number of GPs per clinic) and by population density of each ED.

Figure 1 The weighted spatial distribution of GP services for each ED, by the population density of each ED



In the next section we demonstrate how we can use spatial interaction models (SIM) to extend the analysis outlined above. Combining the access scores produced by the SIM with our logit results allows one to examine whether the spatial distribution of GP services matches the spatial distribution of demand for health care service.

4. Modelling Accessibility

Spatial interaction models (SIM) have a long tradition of being used to estimate flows of people to service outlets (Birkin and Clarke, 1991; Fotheringham and O'Kelly, 1986; Yano et al., 2000). For different consumers, one can model the trade-off between spatial convenience (visiting an outlet close by) and the attractiveness of particular outlets (measured by proxies such as size, brand and quality of the service). Although there is a classical family of spatial interaction models (Wilson, 1974), one model, the production-constrained SIM, has dominated the literature (Fotheringham et al., 2001 and Clarke et al., 2002). These models allow the user to estimate the trip end totals (revenue in shopping models, number of patients attending hospital or GP surgery in health care models) and thus serve as location models.

From the outputs of these models it is possible to build a suite of performance indicators to measure how well served residents are for the service under consideration (Clarke and Wilson, 1994 and Clarke et al., 2002). Thus, these models quantify accessibility according to where individuals consume services as predicted by the SIM and as such provide a more realistic representation of access to services than, for example, simply taking the number of service outlets in a zone or estimating accessibility through a simple straight-line nearest facility type indicator. Such a model can be written as:

$$T_{ij} = O_i A_i W_j \exp(-\beta d_{ij}) \qquad (5)$$

where T_{ij} is the flow of individuals from residential zone *i*, to each service centre *j*, O_i is the demand for the service in ED *i*, W_j is the attractiveness of outlet *j*, d_{ij} is the distance from the origin, *i* to the destination, *j*, β is a distance decay parameter and A_i is a balancing factor that ensures that,

$$\sum_j T_{ij} = O_i \tag{6}$$

A_i is calculated as:

$$A_i = \frac{1}{\sum_j W_j \exp(-\beta \, d_{ij})} \tag{7}$$

Taking the results from the SIM, two effectiveness indicators may be used to predict access scores for each small area (Clarke et al, 2002). The first effectiveness indicator calculates the aggregate provision of a service for an area and is defined as follows:

$$w_i = \sum_j \frac{T_{ij}}{T_{*j}} W_j \tag{8}$$

The second indicator is:

$$v_i = \frac{w_i}{I_i} \tag{9}$$

whereby the aggregate provision of each zone *i* is divided by the total number of residents in the zone (I_i). Using these performance indicators prevents areas with a small population or no services being automatically labelled as 'poor access areas', when in fact these areas may reside close to neighbouring zones with good access (the interaction based indicators provide a type of smoothing effect).

In this paper the SIM described above is used to measure access scores from each ED to their nearest GP centre. For the purpose of this paper the attractiveness parameter for each health care centre, W_j is the number of practitioners in each health centre (a measure of how easy it is to be examined quickly). The demand variable, O_i is the potential demand for GP services as estimated by the logit model outlined previously. The distance variable, d_{ij} is the distance from each ED centroid (i), to each primary care service *(j)*. D_{ij} was calculated using network analysis (using the current road data for Ireland) in ArcGIS. Combining the results from the logit model and the access score from the SIM will highlight areas with low GP accessibility given their health status.

5. Results

As outlined in section 3, there is considerable research on the individual attributes that affect the decision to utilise a GP surgery at the national level in Ireland. For this analysis, the relationship between GP attendance and individual location and characteristics was examined by running separate logit models for each ED. Given that there are 238 EDs in the county the results of each logit model are not presented. However, table 4 presents the results (coefficient values and their associated standard errors and marginal effects) of a logit model for County Galway as a whole. With a value of 38311, the log likelihood $\chi 2$ statistic shows that, taken jointly, the coefficients in our preferred logit model are significant at the 1% level. The coefficients were also found to be individually significant and of the expected sign.

On average, it was found that the main drivers of GP utilisation in county Galway were; income (the probability of attending a GP service increases 1% for each additional unit decrease in household income), medical card status (those eligible for free public health care are 12% more likely to use a GP service than those who are not eligible), marital status (married individuals were 18% more likely to use a GP service single individuals) and the presence of a long-term illness (those with a long-term illness are 30% more likely to use a GP than those without).

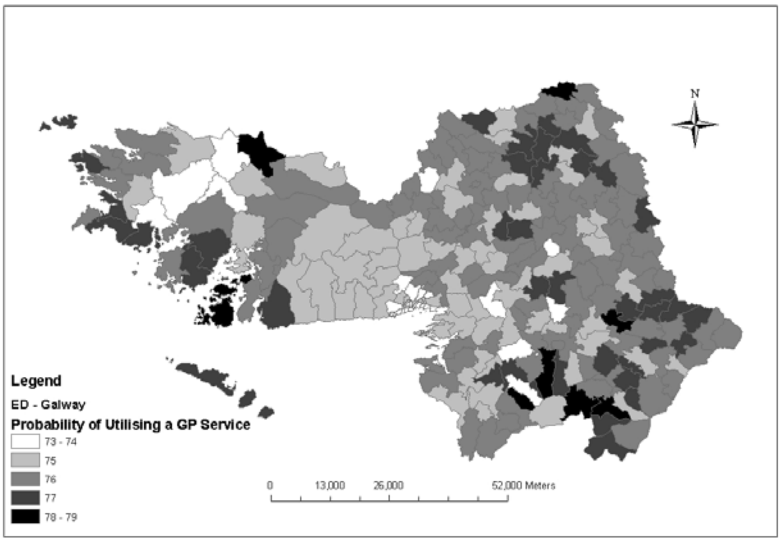
Table 4 Logit Model Results of utilisation of GP services for the residents of Co. Galway

GP Attendance	Coefficient	Standard Error	Marginal Effect
Net Household Income (Ire£)	-0.080	-0.003*	-0.017
Marital Status (0 - married, 1- single)	-0.753	-0.094*	-0.180
Age	0.030	0.001*	0.007
Medical Card Status (0 - no Medical Card, 1- Have Medical Card)	0.592	0.017*	0.121
Gender (0 - Male, 1- Female)	0.415	0.011*	0.090
Long term Illness (0 - No, 1- Yes)	1.939	0.027*	0.305
No Primary Education	0.742	0.130*	0.142
Primary Education	1.088	0.129*	0.199
Lower Secondary Education	1.369	0.129*	0.243
Higher Secondary Education	0.944	0.129*	0.193
Lower Third Education	1.465	0.129*	0.251
Higher Third Education	1.431	0.132*	0.223
Own Private Car (0 - No, 1- Yes)	0.023	0.020**	0.005
Constant	-1.824	-0.1318*	
No. of Individuals (above the age of 16)	169806		
Pseudo R^2	0.170		
Likelihood Ratio χ^2 Statistic	38311		

Unsurprisingly, it was also found that females are 9% more likely to use a GP service than men. Also significant and found to positively effect GP utilisation was higher education levels. Given that the base case for education is special needs education it is surprising that the other education categories are positive. This may be as a result of the relatively small number of individuals represented in the base category. Owning a car would appear to only marginally increase the probability of GP attendance.

The spatial distribution of the mean probability of attending a GP for each ED was estimated using each EDs separate logit models results. These probabilities are provided in Figure 2. As one can see from Figure 2 the more rural parts of Galway (in the West and East of the county) have the highest predicted probabilities of GP utilisation.

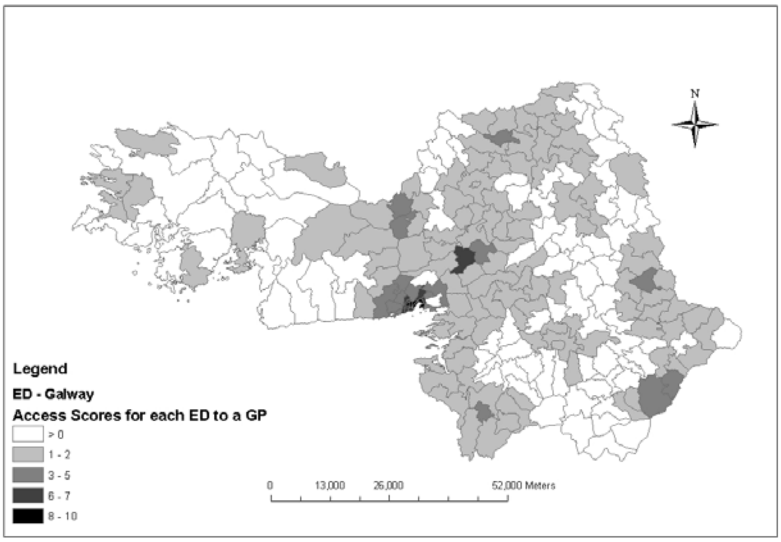
Figure 2 The mean probability of an individuals in each ED using a GP service as estimated by separate ED level Logit Models



It is interesting to note the difference between simulated GP utilisation and potential GP utilisation. The number of visits and associated confidence interval (CI) for simulated 'real' GP utilisation in Galway was 1226.6 (1220.7, 1232.4) and the equivalent figure for potential GP utilisation was 1847.0 (1840.5, 1856.1). For the potential utilisation figures, individuals with a predicted probability greater than 0.5 are assigned a value of 1 (i.e. the individual attends a GP), while those with a probability of less than 0.5 are assigned a value of 0 (i.e. the individual does not attend a GP). As one can see, the confidence intervals do not overlap. Also, the potential number of individuals who utilise GP services is much higher than the real GP utilisation number. This indicates that potential demand for GP services is much higher than revealed (simulated) demand and that we are justified in using potential rather than 'real' demand.

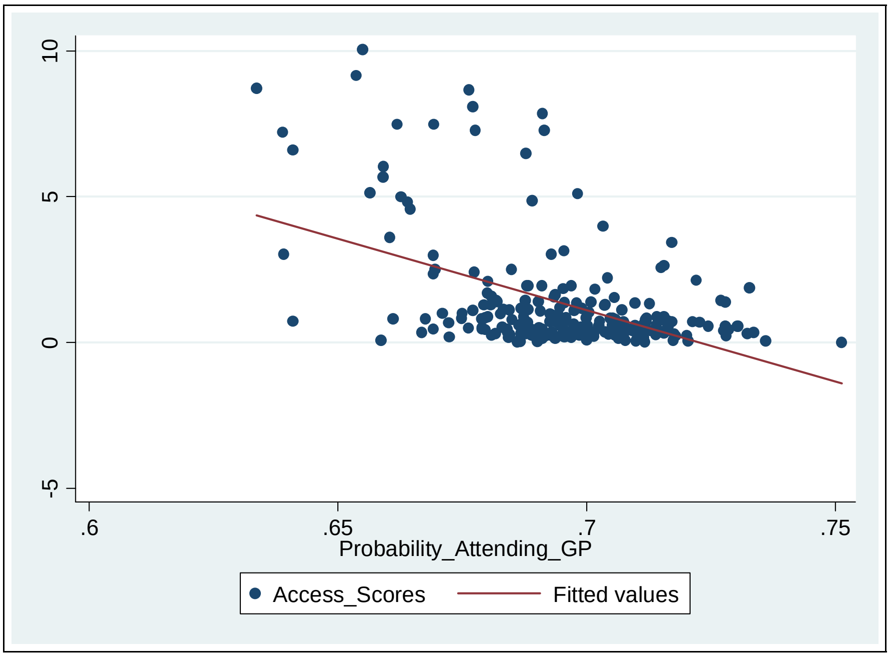
Using the two performance indicators specified in section 4, the access scores for EDs in relation to GP services were calculated for Co. Galway. The access score for each ED in Co. Galway ranged from 0.001 (indicating very poor access) on the south west coast of Galway to 38.87 (indicating very good access) within Galway city, while the average access score across the 238 EDs was 2.39. The accessibility scores for each ED with regard to GP services are presented in Figure 3.

Figure 3 Access Scores for each ED to a GP service in County Galway as calculated by the Accessibility Indicators



Finally, we compare the weighted access indicators scores from the spatial interaction model for County Galway to the weighted mean predicted probabilities of the residents of each ED attending a GP service. Figure 4 presents a scatter-plot graph comparing the mean probability of attending a GP for each ED with the mean accessibility scores for each ED. As one can see from the scatter plot, EDs with the highest probability of attending a GP, given the characteristics of their individual residents, actually have the lowest accessibility to GP services. Conversely, one can see from the scatter-plot that for the EDs with the lowest probability of using a GP service, the residents have the highest accessibility to a GP service.

Figure 4 Comparison of the mean probability of attending a GP for each ED with the mean accessibility scores for each ED



Consistent with previous research (Hart, 1971) our results indicate that there is an inverse relationship between health care need and health care provision at the sub-national level in Ireland. That is, the distribution of GP services in county Galway is least accessible to those that need the service most. It is the combination of the SIM and the spatial microsimulation model that allows us to carry out this analysis; an analysis that would be very difficult to accomplish otherwise.

6. Conclusions

This paper set out to estimate the demand for GP services across urban and rural areas and establish whether or not the spatial distribution of GP services matched the spatial distribution of demand. As we can see from the logit analysis, the demand for GP services is much higher in rural Galway than urban Galway. These results are perhaps unsurprising given the higher elderly population living in rural Ireland. However, the output from the SIM shows that rural areas have the lowest access to GP services. These results are consistent with findings in the UK and other European countries and point to the existence of an inverse relationship between health care need and health care provision. That is, the distribution of GP services is least accessible to those that actually need the services.

The second objective of this paper was to use micro-level rather than aggregate level data to examine the need for GP utilisation across rural and urban areas. Geographical considerations play a crucial role in influencing health. Geography may directly affect an individual's health status; through one's environment or, less tangibly, through effects such as an area's social capital and service availability. Traditionally, rural areas were seen as healthier, almost idyllic areas to reside, compared to urban areas. However, recent research by Haynes and Gale (2002) and Barnett et al., (2002) have shown that variations in health status in rural communities is apparent not at the area level, but at the individual level.

Our results have two main implications for policy and research. First, with regard to resource allocation, the obvious mismatch between service need and service availability indicates that governments need to employ some method of allocating resources more efficiently across space in response to potential health service demand. Second, from a methodological perspective, we show that the use of aggregate indicators for the measurement of health service demand across space may be inappropriate, specifically when dealing with smaller, dispersed populations such as rural areas. Thus, this paper demonstrates that a spatial microsimulation model, when combined with a spatial interaction model, can indicate areas with high health care demand and poor health care access. These results in turn can be used to target health care resources in areas with the highest demand and lowest access and therefore optimise government intervention and public resources in a more effective manner.

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