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MODELLING HOSPITAL ACTIVITY: ACCOUNTING FOR SMALL AREA AND PRIMARY CARE PRACTICE VARIATION

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Abstract

Management of care in appropriate settings - for example, avoiding unnecessary attendances at hospital A&E units that could be handled in primary care - is an important part of health strategy. Hence methods are required to identify sources of excess attendances both geographically and in terms of primary care practices responsible for patients. This paper considers a Bayesian random effects approach to modelling small area and GP practice variation in hospital attendances or admissions with a view to detecting outlier areas or practices with unduly high rates. The model allows for the impact on small area attendance rates of deprivation and geographic access (to both primary care and to hospitals) and also for the interplay between small area health demand and the population distribution between GP practices. The case study involves a six month survey of A&E attendances at a North London Hospital by residents in a London Borough. It considers relativities in attendance rates between 149 small areas in this borough in relation to area deprivation scores and differential geographic access to GP surgeries, while also allowing for variation in attendance rates across the 53 GP practices in the case study area.

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1. Introduction

Containment of emergency admissions is a major element in current strategic management of acute (i.e., hospital based) health demand. Unplanned emergency admissions and attendances at hospital A&E clinics are closely related. Often such attendances or admissions are avoidable given timely and appropriate care in a primary setting (Weissman et al. [21]; Lin et al. [14]). However, GP practices may vary in their effectiveness in providing such care. Of particular importance in strategic management of the primary-acute care interface is identification of small areas and GP practices that have above average A&E attendance levels and emergency admission rates.

This paper proposes a fully Bayesian modelling strategy that allows for the impact on small area attendance rates of area social structure (e.g., area deprivation), geographic accessibility to both primary care and hospitals with A&E units, and the impact of variations in GP practice effectiveness - where low effectiveness would be demonstrated by an attendance rate in a practice's population exceeding that expected given that population's socio-economic and age profile.

Access to primary care is important in reducing avoidable admissions or attendances at hospitals (Guagliardo [10]; Gulliford [11]). In the UK health system, patients may choose their GP practice and there are no geographic constraints on their choice, so the patients of small area i are typically affiliated to a range of practices, though in practice geographic access to the GP surgery affects affiliation rates. Although there are well-known effects of deprivation on health demand by area (Carstairs [4]), various factors influencing attendance rate variations between areas may be unobserved. The area modelling strategy in this paper therefore includes an allowance for spatially correlated but unobserved risk factors; these are modelled by an intrinsic conditional autoregressive prior (Besag et al. [2]).

Attendance variations are considered both by area i $(i = 1, \ldots, I)$ and GP practice j $(j = 1, \ldots, J)$ in a bivariate framework. So attendances Y_{1i} by area, and Y_{2j} by practice, are separate outcomes. However, the model for areas includes a weighted average of practice effects, where the weights are determined by known affiliation rates a_{ij} (the proportion of area *i* patients affiliated to practice *j*).

An alternative framework considered by Congdon and Best [5] considers a crossed structure where the units for the response are formed by (i, j) pairings; hence there are potentially $L = IJ$ observations. Since in fact many cells in the $I \times J$ cross-classification of patients by practice are empty (e.g., because practice *j* is too geographically remote from area *i* to attract any patients from it), this alternative model approach in fact uses a subset of the *L* possible area-practice intersections. Such a subset might be defined in terms of patient catchment thresholds (e.g., only include area-practice cells when a practice accounts for at least 1% of an area's population). In the model used in the present paper this problem is avoided since empty cells are automatically discounted.

The model used here has some similarities to the Poisson-gamma spatial framework suggested by Wolpert and Ickstadt [22], whereby the model for area *i* rates includes a weighted sum of effects of rates in other areas. Their framework assumes an additive risk model for the Poisson mean risk in area *i* that constrains the effect of risk factors (e.g., area deprivation) to be positive. Here a log link is used for the Poisson means of Y_1 and Y_2, so such a constraint is not needed. The work here also relates to disease mapping models for area to hospital flows that include gravity principles (e.g., Dreassi and Biggeri [6]), though in the present analysis the observations relate to only one hospital destination. The model of the present paper is distinct in including cross-cutting effects for both the area of residence of diseased persons and their primary care practice.

A case study analysis uses data on 20186 attendances at Oldchurch Hospital in North East London during April 1 to September 30, 2003, and focuses on attendances at this hospital by residents of the outer London borough of Havering who are also affiliated to the 53 GP practices sited within Havering (Oldchurch hospital is located in central Havering). The 20186 attendances account for a large majority (86% in a total of 23389) of the attendances at Oldchurch in this six month period. This implies an annualised crude attendance rate (in relation to Havering's population of around 225000) of 180 per 1000. Peak demand in terms of age specific attendance rates is in young children and the old (Figure 1).

2. Model for Geographical and Practice Variations

The geographical unit of analysis is the recently introduced Special Output Area, designed by the UK Office of National Statistics Census Unit in consultation with local agencies to approximate to meaningful local neighbourhoods and communities. There are 149 such SOAs in Havering with an average population P_i of 1500; these are subdivisions of 17 electoral wards. Analysis at the ward level shows a strong association between standardised attendance rates and deprivation, measured by IMD2004 scores (an abbreviation for Index of Multiple Deprivation for 2004) (Noble et al. [16]). Table 1 shows the highest all ages attendance ratios (these are age standardised ratios of actual to expected attendances) are in Gooshays, Heaton and South Hornchurch wards (see Figure 2 for electoral ward configuration and quintile map of attendance ratios) while the lowest is in Upminster. The correlation of the standard attendance ratios with the IMD score is 0.85.

Variations at SOA level are wider, with the maximum likelihood all ages attendance rates varying from 54 to 164. There is a positive correlation (of 0.65) between SOA attendance rates and their IMD scores. However, such ML estimates may be based on relatively small numbers and do not take account of spatial correlation in adjacent rates. Here a random effects model is used to model attendances Y_{1i} in the ith SOA according to deprivation (Z_{1i}), Euclidean distance to the case study hospital (R_i) and access to primary care. An access score A_i is based on the Euclidean distances d_{ij} between SOAs and the GP practices $j = 1, \dots, J$ $(J = 53)$ that are based in Havering. This score takes account of the number M_j of GPs in each GP practice. Thus

$$A_i = \sum_{j=1}^{J} M_j f(d_{ij}), \tag{1}$$

where $f(d)$ is a declining function of the distance d_{ij} between the population centroid of area i and the location of the surgery of practice j. It is expected that an analysis based on travel times as opposed to Euclidean distance would give similar results. Use of travel times is problematic as attenders may use one of several alternative modes, and additionally Euclidean distances tend to be strongly correlated with travel times (Phibbs and Luft [17]).

It is also necessary to take account of the impact on small area attendance rates of variations in primary care effectiveness. This involves a bivariate model in which the same data is modelled both in terms of its spatial pattern and in terms of its variation over GP practices. Thus let Y_{2j} denote attendances by GP practice. Also let $a_{ij} = P_{ij}/P_i$ denote the proportion of the population of the ith small area which is affiliated to practice j. In fact in the current application a small number of area i patients, say $P_{i,out}$, are registered with GP practices located outside Havering, and the a_{ij} are then obtained as $a_{ij} = P_{ij}/(P_i - P_{i,out})$.

Several factors may impact on primary care effectiveness. However, an important influence to control for is the deprivation level Z_{2j} in the population affiliated to practice j. Often relatively good or bad 'performance' indicators for schools, hospitals, local authorities, etc. result in part from the social structure of their population (e.g., Andrews et al. [1]). There will also be many unobserved influences on primary care effectiveness that are here summarised in a practice level random effect. Then the model for GP practice variation assumes Poisson variation

$$Y_{2j} \sim Po(E_{2j}\nu_j), \quad j = 1, \ldots, J, \tag{2a}$$

where E_{2j} are expected attendances (based on the GP practice's population age and sex structure) with

$$\log(\nu_j) = \beta_1 Z_{2j} + e_j, \tag{2b}$$

where e_j are Normal random effects with mean which is the regression intercept β_0 and variance $1/\kappa_e$, $e_j \sim N(\beta_0, 1/\kappa_e)$. Taking e_j to have the intercept as their mean alleviates an identifiability issue discussed by Vines et al. [19], Gelfand et al. [8] and Knorr-Held [12].

To define the area model, let s_i denote spatially correlated and unmeasured influences on morbidity. These are centred to have mean zero (so avoiding a problem with separately identifying the intercept). They are assumed to follow a Normal conditional prior

$$s_i \mid s_{[i]} \sim N\left(S_i, \frac{1}{N_i \kappa_s}\right) \tag{3}$$

with mean S_i and variance $1/(N_i \kappa_s)$, where N_i is the number of neighbours of area i, where $s_{[i]} = (s_1, s_2, \ldots, s_{i-1}, s_{i+1}, \ldots, s_I)$, and $S_i = \sum_{j \in L_i} s_j / N_i$ is the average of the spatial effects in the locality L_i of area i. The influence of practice effectiveness variation on the small area attendance rate is summarised by a weighted sum of practice means from the model in (2), namely,

$$C_i = \sum_{j=1}^{J} a_{ij} \nu_j. \tag{4}$$

Then the model for attendances by area (the 149 SOAs) is

$$Y_{1i} \sim Po(E_{1i} \mu_i) \tag{5a}$$

with

$$\log(\mu_i) = \gamma_0 + \gamma_1 Z_{1i} + \gamma_2 A_i + \gamma_3 R_i + \gamma_4 C_i + s_i, \tag{5b}$$

where expected attendances E_{1i} are based on applying the age-sex rates for the entire region (Havering) to the populations of SOAs.

Of particular interest is whether practice effects, as represented in the filtered sum (4), have any impact on area relativities μ_i in attendance rates, particularly after spatial effects s_i have been introduced for each SOA. Therefore, two models are compared, the first excluding s_i in (5b), the second including such effects.

3. Relevant Model Outputs: Area Level Discrepancies between Attendance and Access and a Practice Level Performance Index

Measures to reduce high attendance rates may involve provision of extra local facilities or primary care staff and the siting of such resources is important. A possible index of poor access in relation to health care need is the discrepancy between the attendance rate μ_i and the level of access to primary care in an SOA. The latter is measured by the ratio of access in SOA i to average access in all SOAs $A_i/\overline{A}$. So

$$D_{1i} = \mu_i - A_i/\overline{A} \tag{6a}$$

is a measure suggesting where demand for A&E attendances might be reduced by improving access to primary care. High discrepancies will occur when a high attendance rate is combined with access below average.

GP practice efficiency and organisation (e.g., appointments systems, out of hours availability) may affect A&E attendance rates. A possible performance measure is provided by the discrepancy between the practice attendance rate and its practice deprivation score taken relative to the region (Havering wide) average; so

$$D_{2j} = \nu_j - Z_{2j}/\overline{Z}_2. \tag{6b}$$

4. Model Estimation and Priors

Relatively diffuse $N(0, 100)$ priors are used for the fixed effects $\{\beta_0, \beta_1, \gamma_0, \gamma_1, \gamma_2, \gamma_3, \gamma_4\}$ while-gamma priors with scale and index 1 are used for the precisions κ_s and κ_e. In the access scores (1), $f(d_{ij})$ is assumed to be of the exponential decay form

$$f(d_{ij}) = \exp(-hd_{ij}) \quad h > 0, \tag{7}$$

where values of h are typically under 0.5. For example, Carr-Hill et al. [3] assume $h = 0.2$. Here a ten point discrete prior with values $h = 0.1, 0.2, ..., 0.9, 1$ is assumed using precalculated decay matrices at these values. One might model h as a continuous unknown but at the cost of considerably greater computing times because the repeated calculation of $f(d_{ij})$ involves a 149×53 distance matrix. Fit is measured using the DIC criterion of Spiegelhalter et al. [18]. Estimation uses two chains with dispersed initial values run for 10000 iterations. Convergence was assessed by Gelman-Rubin criteria (Gelman et al. [9]) and summaries of parameters and discrepancy indices D_{1i} and D_{2j} are based on iterations 5,000-10,000.

5. Results

The model comparison involves the DIC using deviances as minus twice likelihoods. The deviance as defined by McCullagh and Nelder [15] is also obtained (and denoted the GLM deviance in Table 2) as this indicates how successfully the model has tackled overdispersion in the data. These fit measures accumulate over the sub-models for practices (equation (2)) and areas (equation (5)).

Table 2 shows that the model including spatial effects considerably improves the fit, as measured by the DIC, but at the cost of an increase in effective parameters. The GLM deviance is much more in line with the total of observations (149 areas plus 53 practices). Coefficient summaries show that the parameter γ_4 is much reduced in model 2 when spatial effects s_i are included; in fact the 2.5% point for γ_4 is slightly negative though the 90% credible interval is entirely positive.

By contrast, allowing for idiosyncratic area effects considerably enhances the distance effect to hospital, γ_3. The coefficients γ_1 and β_1 reflecting the impact of deprivation are both significant, though β_1 is enhanced in model 2. The impact of access to primary care (increases in which might be expected to reduce unnecessary A&E attendances), as summarised in the parameter γ_2, is also enhanced in model 2. In both models the discrete prior for h in $f(d_{ij})$ concentrates on small values, with $h = 0.2$ being the modal value in model 2.

Of particular interest in health strategy terms are outlier areas and practices, particularly if excess hospital attendances by area coincide with poor access to primary care, and if high attendance rates by practice are discrepant with the practice population profile. Table 3 lists posterior means and 95% intervals for practice effects ν_j under model 2, their practice population deprivation scores, and the practice level discrepancies, as in (6b). The highest practice attendance ratio is 187 whereas that practice's deprivation score is not markedly high. Figure 3 shows the distribution of high discrepancies (6a) at area level and shows how these are typically sub-areas of the electoral wards with highest attendance rates (Figure 1), suggesting a form of "inverse care"-high need compounded by relatively poor access to primary care (e.g., Furler et al. [7]).

6. Discussion

This analysis has suggested a methodology for assessing possible area and GP practice outliers in relation to A&E attendances at hospitals. Such attendances are often assessed as unnecessary, involving conditions that could be treated in primary care settings. Among GP practices, two practices have high attendance rates in relation to the deprivation level of their catchment populations (practices 35 and 42 in Table 3).

Often efforts to improve primary care and to reduce costly but avoidable hospital referrals or attendances involve more than one type of outcome. For example, emergency admissions to hospital have been increasing in the UK and are often rated as avoidable. One might generalise the model framework in Section 2 to involve several outcomes, each with a bivariate (area and practice) sub-model. For example, let Y_{11i} denote area level emergency admissions and Y_{12j} denote their configuration over GP practices; similarly let Y_{21i} denote area level A&E attendances and Y_{22j} denote their practice configuration. Then a model structure could take the form

$$Y_{m1i} \sim Po(E_{m1i}\mu_{mi}) \quad m = 1, 2, i = 1, \ldots, I,$$

$$Y_{m2j} \sim Po(E_{m2j}\nu_{mj}), \quad m = 1, 2, j = 1, \ldots, J,$$

where E_{m1i} are expected outcomes by area, and E_{m2j} are expected outcomes by GP practice, with model means

$$\log(\mu_{mi}) = \gamma_{0m} + \gamma_{1m} Z_{1i} + \gamma_{2m} A_i + \gamma_{3m} R_i + \gamma_{4m}\left(\sum_{j=1}^{53} a_{ij} \nu_{mj}\right) + s_{mi},$$

$$\log(\nu_{mj}) = \beta_{1m} Z_{2j} + e_{mj}.$$

Possible simplifications would involve common practice or area effects ($s_{mi} = s_i$ and/or $e_{mj} = e_j$), or modelling of such effects by a factor model (Wang and Wall [20]).

To avoid the heavy parameterisation involved in the fully random spatial effects model (4), one might consider alternative spatial priors based on the multiple membership prior of Langford et al. [13]. Thus let u_i denote a spatially unstructured effect linked to the s_i via geographical weights w_{ij} (with $\sum_j w_{ij} = 1$), namely, $s_i = \sum_j w_{ij} u_i$. Then u_i may be generated as a random effect or via a nonparametric prior (e.g., a Dirichlet process) possibly reducing the increase in effective parameters in going from

$$\log(\mu_i) = \gamma_0 + \gamma_1 Z_{1i} + \gamma_2 A_i + \gamma_3 R_i + \gamma_4\left(\sum_{j=1}^{J} a_{ij} \nu_{mj}\right)$$

to

$$\log(\mu_i) = \gamma_0 + \gamma_1 Z_{1i} + \gamma_2 A_i + \gamma_3 R_i + \gamma_4\left(\sum_{j=1}^{J} a_{ij} \nu_{mj}\right) + s_i.$$

Finally, many urbanised areas have a choice of providers (e.g., general hospitals with A&E units). If observations Y_{ik} (such as A&E attendances) are available by relevant providers $k = 1, \ldots, K$, then the area model (5b) can be provider specific, with distances R_{ik} specific to each area and provider. Intercepts and spatial effects may also be provider specific, as in

$$Y_{ik} \sim Po(E_{1i} \mu_{ik})$$

$$\log(\mu_{ik}) = \gamma_{0k} + \gamma_1 Z_{1i} + \gamma_2 A_i + \gamma_3 R_{ik} + \gamma_4\left(\sum_{j=1}^{J} a_{ij} \nu_j\right) + s_{ik}.$$

References

[1] R. Andrews, G. Boyne and R. Walker, Deprivation and Local Authority Performance: the Implications for CPA, Centre for Local and Regional Government Research, Cardiff University (CLRGR Discussion Paper No. 10), 2004.

[2] J. Besag, J. York and A. Mollie, Bayesian image restoration with two applications in spatial statistics, Ann. Inst. Statist. Math. 43 (1991), 1-59.

[3] R. Carr-Hill, G. Hardman, S. Martin, S. Peacock, T. Sheldon and P. Smith, A formula for distributing NHS revenues based on small area use of hospital beds, Centre for Health Economics, University of York, Occasional Paper 22, 1994.

[4] V. Carstairs, Deprivation indices: their interpretation and use in relation to health, J. Epidemiol Community Health 49 (Suppl) (1995), S3-8.

[5] P. Congdon and N. Best, Small area variation in hospital admission rates: adjusting for referral and provider variation, J. Roy. Statist. Soc. Ser. C 49 (2000), 207-226.

[6] E. Dreassi and A. Biggeri, Incorporating gravity model principles into disease mapping, Biom. J. 45 (2003), 207-217.

[7] J. Furler, E. Harris, P. Chondros, P. Powell Davies, M. Harris and D. Young, The inverse care law revisited: impact of disadvantaged location on accessing longer GP consultation times, Med. J. Aust. 177 (2002), 78-79.

[8] A. Gelfand, S. Sahu and B. Carlin, Efficient parameterizations for normal linear mixed models, Biometrika 82 (1995), 479-488.

[9] A. Gelman, J. Carlin, H. Stern and D. Rubin, Bayesian Data Analysis, 2nd ed., CRC Press, 2003.

[10] M. Guagliardo, Spatial accessibility of primary care: concepts, methods and challenges, Internat. J. Health Geographics 3 (2004), 1-13.

[11] M. Gulliford, Availability of primary care doctors and population health in England: is there an association?, J. Public Health Medicine 24 (2002), 252-254.

[12] L. Knorr-Held, Bayesian modelling of inseparable space-time variation in disease risk, Statistics in Medicine 19 (2000), 2555-2567.

[13] I. Langford, A. Leyland, J. Rasbash and H. Goldstein, Multilevel modelling of the geographical distributions of diseases, J. Roy. Statist. Soc. Ser. C 48 (1999), 253-268.

[14] G. Lin, D. Allan and M. Penning, Examining distance effects on hospitalizations using GIS: a study of three health regions in British Columbia, Canada, Environment and Planning A 34 (2002), 2037-2053.

[15] P. McCullagh and J. Nelder, Generalized Linear Models, Chapman & Hall/CRC, 1989.

[16] M. Noble, G. Smith, B. Penhale, G. Wright, C. Dibben and M. Lloyd, Measuring Multiple Deprivation at the Small Area Level: The Indices of Deprivation 2000, Dept. of Environment, Transport & Regions, Regeneration Series Reports, December 2000.

[17] C. Phibbs and H. Luft, Correlation of travel time on roads versus straight line distance, Medical Care Research and Review 52 (1995), 532-542.

[18] D. Spiegelhalter, N. Best, B. Carlin, A. van der Linde, Bayesian measures of model complexity and fit, J. Roy. Statist. Soc. Ser. B 64 (2002), 583-639.

[19] S. Vines, W. Gilks and P. Wild, Fitting Bayesian multiple random effects models, Stat. Comput. 6 (1996), 337-346.

[20] F. Wang and M. Wall, Generalized common spatial factor model, Biostatistics 4 (2003), 569-582.

[21] J. Weissman, C. Gatsonis and A. Epstein, Rates of avoidable hospitalization by insurance status in Massachusetts and Maryland, J. American Medical Association 268 (1992), 2388-2394.

[22] R. Wolpert and K. Ickstadt, Poisson/gamma random fields models for spatial statistics, Biometrika 85 (1998), 251-267.

Table 1. Attendance ratios by ward

Ward	Attendances	SAR	IMD2004
Brooklands	1144	1.00	18.45
Cranham	864	0.80	6.87
Elm Park	1192	1.04	16.93
Emerson Park	944	0.93	8.47
Gooshays	1811	1.32	31.60
Hacton	946	0.89	10.55
Harold Wood	1261	1.17	18.03
Havering Park	1165	1.02	18.64
Heaton	1381	1.23	26.59
Hylands	1128	1.02	11.32
Mawneys	1130	0.98	16.06
Pettits	951	0.81	9.89
Rainham & Wennington	1000	0.91	17.39
Romford Town	1185	1.00	16.43
St Andrew's	904	0.82	11.89
South Hornchurch	1268	1.27	20.56
Squirrel's Heath	1121	1.05	9.76
Upminster	791	0.70	6.48

Table 2. Parameter estimates, models with and without spatial random effects

	Parameter	Mean	2.5%	5%	95%	97.5%
Model 1	γ_0	0.398	0.028	0.050	0.804	0.824
(No spatial effects)	γ_1	0.181	0.149	0.154	0.208	0.213
	γ_2	–0.408	–0.786	–0.772	–0.101	–0.084
	γ_3	–0.154	–0.202	–0.196	–0.115	–0.110
	γ_4	0.575	0.467	0.484	0.668	0.684
	β_0	–0.404	–0.631	–0.604	–0.187	–0.158
	β_1	0.307	0.125	0.133	0.465	0.474
DIC	2044					
Effective Parameters	57					
GLM Deviance (Posterior Mean)	595					
	Parameter	Mean	2.5%	5%	95%	97.5%
Model 2	γ_0	0.855	0.324	0.369	1.262	1.293
(Including spatial effects)	γ_1	0.205	0.134	0.148	0.268	0.284
	γ_2	–0.592	–0.952	–0.933	–0.198	–0.182
	γ_3	–0.476	–0.607	–0.589	–0.357	–0.333
	γ_4	0.260	–0.002	0.042	0.472	0.514
	β_0	–0.431	–0.622	–0.591	–0.287	–0.257
	β_1	0.330	0.234	0.242	0.476	0.487
DIC	1751					
Effective Parameters	160					
GLM Deviance (Posterior Mean)	200					

Table 3. Practice attendance relativities and discrepancy measures

	ν_j		D_{2j}		
Practice	Mean	St devn	Mean	St devn	Practice Population Deprivation
1	0.74	0.04	0.28	0.04	7.0
2	0.67	0.03	0.22	0.03	6.9
3	1.43	0.03	0.41	0.03	15.7
4	0.92	0.03	0.06	0.03	13.4
5	0.90	0.03	–0.02	0.03	14.2
6	1.23	0.04	–0.56	0.04	27.5
7	1.08	0.04	0.01	0.04	16.5
8	0.84	0.03	–0.06	0.03	13.9
9	1.05	0.04	–0.71	0.04	27.1
10	1.32	0.05	–0.46	0.05	27.5
11	1.65	0.20	0.48	0.20	18.1
12	0.95	0.05	–0.04	0.05	15.3
13	1.11	0.04	0.38	0.04	11.3
14	1.06	0.03	0.13	0.03	14.3
15	0.96	0.05	–0.09	0.05	16.4
16	0.98	0.03	–0.13	0.03	17.2
17	0.24	0.03	–0.85	0.03	16.8
18	0.84	0.06	0.19	0.06	10.1
19	1.62	0.13	0.52	0.13	17.1
20	1.01	0.06	–0.21	0.06	18.9
21	1.35	0.26	0.19	0.26	17.8
22	0.98	0.06	0.50	0.06	7.4
23	0.77	0.05	0.09	0.05	10.6
24	1.08	0.08	–0.05	0.08	17.4
25	0.77	0.07	0.32	0.07	6.8

26	0.93	0.06	0.20	0.06	11.3
27	0.93	0.06	–0.11	0.06	16.0
28	1.09	0.08	–0.10	0.08	18.4
29	1.19	0.08	0.20	0.08	15.3
30	0.54	0.05	–0.72	0.05	19.4
31	0.74	0.07	–0.07	0.07	12.4
32	0.19	0.04	–0.73	0.04	14.2
33	0.63	0.05	–0.01	0.05	9.9
34	0.97	0.08	–0.06	0.08	15.9
35	1.86	0.12	0.72	0.12	17.5
36	1.25	0.07	0.13	0.07	17.3
37	0.86	0.07	–0.27	0.07	17.4
38	1.18	0.06	0.12	0.06	16.4
39	0.80	0.07	0.08	0.07	11.2
40	0.75	0.06	0.28	0.06	7.3
41	0.22	0.03	–0.91	0.03	17.4
42	1.85	0.06	0.78	0.06	16.5
43	1.11	0.06	–0.57	0.06	26.0
44	0.92	0.05	–0.20	0.05	17.4
45	0.87	0.05	0.14	0.05	11.4
46	0.66	0.06	0.16	0.06	7.8
47	1.16	0.07	0.22	0.07	14.6
48	0.70	0.06	–0.12	0.06	12.6
49	1.71	0.10	–0.07	0.10	27.4
50	1.49	0.08	–0.20	0.08	26.2
51	0.89	0.06	0.43	0.06	7.1
52	0.80	0.04	0.12	0.04	10.5
53	0.41	0.05	–0.86	0.05	19.6
Average	0.99		–0.01		15.5

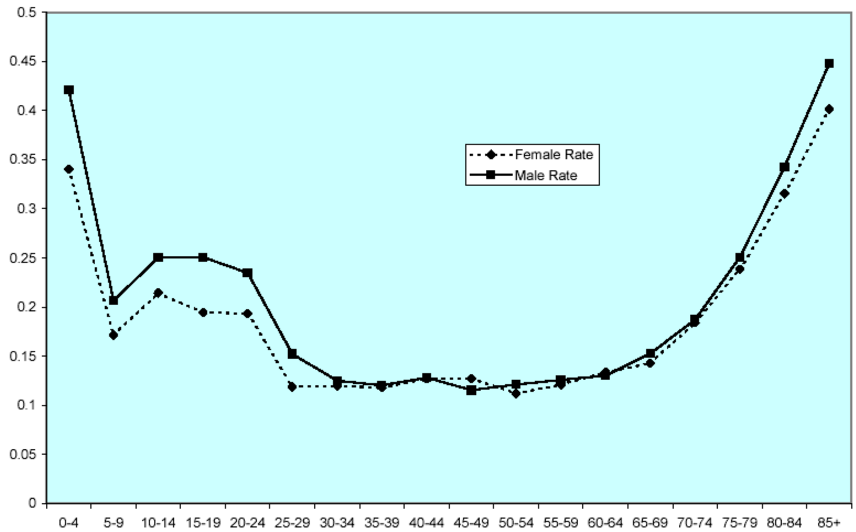

Figure 1. Attendance rate by age.

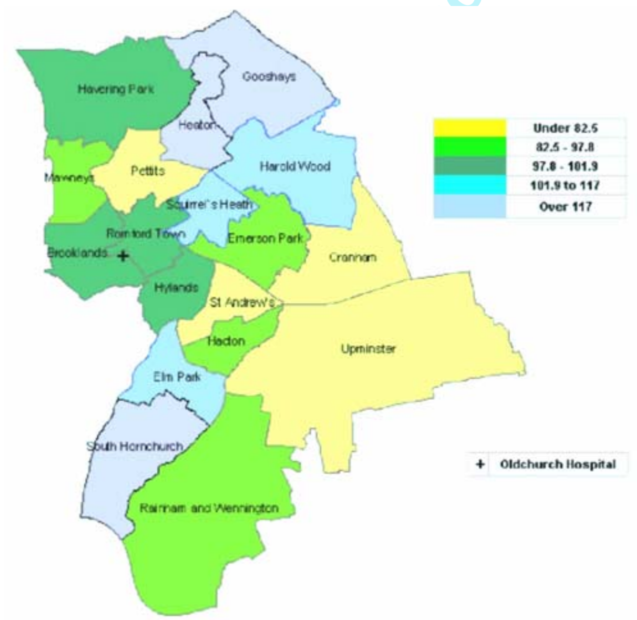

Figure 2. Standard A&E attendance ratios (x 100).

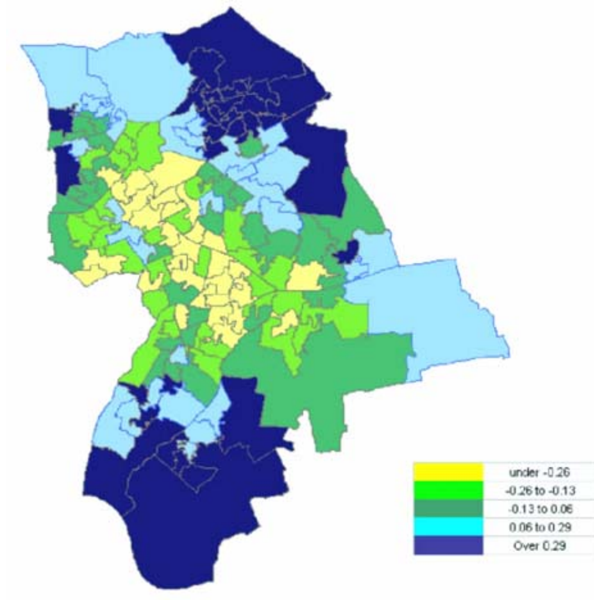

Figure 3. Discrepancies between attendance rates and primary care access.

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