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ORIGINAL ARTICLE

Admission and readmission rate incidences from deprived areas—impact of a classical or multi-dimensional model

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Abstract

Introduction Classical deprivation instruments use a factor analytical approach relying on a smaller number of dimensions, factors or components. Multi-dimensional deprivation models attempt classification in fine detail—even down to street level.

Methods Single-centre retrospective cohort study using routinely collected aggregated and anonymised data on emergency medical admissions (96,526 episodes in 50,731 patients; 2002–2016). We calculated admission/readmission rate incidences for the 74 small areas within the hospital catchment area. We compared a classical Small Area Health Research Unit (SAHRU) to the multi-dimensional POBAL Haase and Pratschke Deprivation Index for Small Areas (POBAL) deprivation instrument and their deprivation ranks for two Irish censuses (2006/ 2011).

Results There was poor agreement between the instruments of the Deprivation Ranks by Quintile—with agreement in 46 and 42% of small areas for the respective 2006 and 2011 censuses. The classical model (SAHRU) suggested more areas with severe deprivation (Q5 66 and 55%) compared with POBAL (Q5 32 and 24%) from the respective censuses. SAHRU classical instrument had a higher prediction level incidence rate ratio (IRR) 1.48 (95% CI 1.47, 1.49)) compared with POBAL IRR 1.28 (95% CI 1.27, 1.28) and systematically lower estimates of hospital admission and readmission rate incidences. Earlier Census data modelled more powerfully, suggesting a long latency between social circumstances and the ultimate expression of the emergency medical admission.

Conclusion Deprivation influences hospital incidence rates for emergency medical admissions and readmissions; instruments focusing at the very small area (individual or street level) have a utility but appear inferior in terms of representing the population risk of environmental/socio-economic factors which seem best approximated at a larger scale.

Keywords Deprivation model · Emergency medical admission · Incidence rates

Introduction

The Central Statistics Office (CSO) calculates deprivation at the individual level by utilising the 11 consensus indicators of deprivation available from their Survey of Income and Living Conditions. Area level deprivation has been defined by Townsend as a state of 'observable and demonstrable disadvantage relative to the local community to which an individual belongs' [1]. Socio-economic deprivation has been shown to increase hospital utilisation [2] and hence healthcare costs [3, 4]. Deprivation is a very significant correlate of the incidence rate of emergency medical admissions [5–7]. Ultimately, although life expectancy has increased over time, irrespective of the level of deprivation within English regions, there has been little improvement in the socio-economic disparities in life expectancy across such regions [8]. Deprivation must therefore be of great interest to practicing clinicians. It is particularly relevant to our catchment area which is predominantly inner city with a high intrinsic of rate of deprivation [9]. We have investigated the influence of Deprivation on the acute 30-day acute hospital mortality [10], readmission rates [11] and hospital costs following an emergency medical admission [12] with emphasis on the population of lower socio-economic status (SES).

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The precise explanation as to why discrete populations experience different healthcare outcomes has been debated; however, the categorisation of deprivation uses physical and social circumstances rather than resources or income and can therefore be distinguished conceptually from poverty [13]. Our traditional Irish Deprivation Index was devised by the Small Area Health Research Unit (SAHRU) investigators (Trinity College, Dublin), using principle components analysis (PCA), a weighted combination (originally five including overcrowding) of four indicators, relating to unemployment, social class, type of housing tenure and car ownership [13]. The methodology is very similar to other classical area deprivation indices, including those by Townsend [1] and Carstairs [14]. Deprivation status for small communities is measured by comparing the standardised differences of selected parameters [15, 16] with the population norms; these parameters can then be related to healthcare (or other) outcome variables [10–12]. With this approach, deprivation indices are based on a factor analytical approach that reduces a larger number of indicators to a smaller number of underlying dimensions, factors, or components.

More recent developments employ a multi-dimensional instrument. Rather than the traditional factor analytical approach, these have been developed based on an a priori conceptualisation of different dimensions of affluence/disadvantage such as Demographic Profile and Social Class Composition and Labour Market Situation. This is the POBAL Haase-Pratschke Instrument [17]. Here, the emphasis is on capturing the fine details at a level of an even smaller area than the Electoral Division. Electoral Divisions (3409 units nationally) in population terms range from under 100 to over 32,000 whereas for the POBAL, instrument data was released for 18,488 small (size standardised) geographical areas with a minimum of 50 households and a mean of just under 100, thus effectively providing street-level information on the Irish population. The move away from the larger Electoral Division towards a much smaller reference unit could represent a major advance, particularly where a census-based deprivation index is used as a proxy for individual-level social position.

In terms of health service planning, however, it is unclear as to how such a change in approach would affect the hospital interest in the rate of presentation of admissions and readmissions from discrete deprivation areas. We therefore have evaluated admission and readmission incidence rates and time trends between 2002 and 2016, using a large database of all emergencies admitted over these 15 years and compared the robustness of the statistical model to predict admission and readmission rate incidences based on the SAHRU and POBAL District Electoral Division ranks from the 2006 and 2011 censuses.

Methods

Background

St. James's Hospital, Dublin serves as a secondary care centre for emergency admissions in a catchment area with a population of 270,000 adults. All emergency medical admissions were admitted from the ED to an acute medical admission unit, the operation and outcome of which have been described elsewhere [18, 19].

Data collection

An anonymous patient database was employed, collating core information of clinical episodes from the Patient Administration System (PAS), the national hospital in-patient enquiry (HIPE) scheme, the patient electronic record, the emergency room and the laboratory systems. HIPE is a national database of coded discharge summaries from acute public hospitals in Ireland [20, 21]. International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) has been used for both diagnosis and procedure coding from 1990 to 2005 with ICD-10-CM used since then. Data included parameters such as the unique hospital number, admitting consultant, date of birth, gender, area of residence, principal and up to nine additional secondary diagnoses, principal and up to nine additional secondary procedures and admission and discharge dates. Additional information cross-linked and automatically uploaded to the database includes physiological, haematological and biochemical parameters.

Deprivation instruments

The Republic of Ireland census (Central Statistical Office) returns report small area population statistics (SAPS); the smallest reporting unit is the Electoral Division (ED). Of the total of 3409, 74 Electoral Divisions are in the hospital catchment area. The catchment area population, measured in 2006, was 210,443 persons, with a median population per ED of 2845 (IQR 2020, 3399). There are two published methods to evaluate deprivation in the ROI; first the Small Areas Health Research Unit (SAHRU) of Trinity College Dublin was responsible for a national census-based small area deprivation index used by the Health Service and other government departments, community groups and academic researchers. The SAHRU Deprivation Index uses methodology similar to Townsend [1] and Carstairs [22] to derive a Deprivation Score, using principle component analysis (PCA), a weighted combination of four indicators, relating to unemployment, social class, type of housing tenure and car ownership [15]. Essentially, a number of parameters considered to reflect deprivation are selected and for each population unit, a score is computed, the numerator being the absolute difference above

or below the national average and the denominator the standard deviation (variance) of the measure. We have previously demonstrated the utility of the SAHRU classification of deprivation in terms of predicting 30-day acute hospital mortality [10], admission and readmission rate incidences [11] and hospital costs following an emergency medical admission [12].

The second method for assessing deprivation at a national level uses a multi-dimensional model and rather than the traditional factor analytical approach (reducing a larger number of indicators to a smaller number of underlying dimensions, factors or components) developed an a priori conceptualisation of these dimensions. Based on earlier deprivation indices for Ireland, as well as analyses from other countries, three dimensions of affluence/disadvantage are identified: demographic profile, social class composition and labour market situation to construct the POBAL Haase-Pratschke measures [17]. Although its main emphasis is to allow study at very small population units, within the three dimensions, each is calculated in the same way for each census wave and then combined to form an Absolute Index Score, allowing the data at the Electoral Division level to be evaluated.

The assignment of patients to small area population units used the ArcGS Geographic Information System software implementation of the well-known point-in-polygon algorithm as outlined by Shimrat [23]. The admission incidence rate (rate/1000 population/year) for our catchment area was calculated by summing admissions for each Electoral Division (i.e. small area for census enumeration purposes) over 15 years and calculating an average for each (numerator) and dividing by the total population within each area (divisor). The readmission incidence rates were similarly calculated, by summing readmissions by the Electoral Division of Residence.

Statistical methods

Descriptive statistics were calculated for background demographic data, including means/standard deviations (SD), medians/inter-quartile ranges (IQR) or percentages. Comparisons between categorical variables and mortality were made using chi-square tests.

We assessed the prediction of outcome (30-day in-hospital mortality considering only one admission per patient—the last episode if > 1 admission) with the previously described predictor variables that included age, acute Illness Severity Score [24, 25], the Charlson Comorbidity Index [26], the Chronic Disabling Score [27] and Sepsis Status [28]. We employed a logistic model with robust estimate to allow for clustering; the correlation matrix thereby reflected the average discrete risk attributable to each of these predictor variables [24]. Logistic regression analysis identified potential mortality predictors and then tested those that proved to be significant univariate predictors ($p < 0.01$ by Wald test) to ensure that the model included all variables with predictive power. Adjusted odds ratios (OR) and 95% confidence intervals (CI) were calculated for those predictors that significantly entered the model ($p < 0.10$). For hospital admission rates, we employed a truncated Poisson regression model, including predictive outcome categorical variables in the model as a series of indicator variables. The dependent variable of the admission rate is a count variable and restricted to certain values; the predictor variables are therefore regressed against admission rates using the zero truncated Poisson model. We used robust standard errors for the parameter estimates, as recommended by Cameron and Trivedi [29]. The Poisson regression coefficients are the log of the rate ratio: the rate at which events occur is called the incidence rate. Thus, with the truncated Poisson regression model, we can interpret the coefficients in terms of incidence rate ratios (IRRs). We regressed the categorisation of Socio-Economic Status by Quintile against the admission rates over time by District Electoral Division (small area) within the hospital catchment area and adjusted for the population age structure (Dependency Ratio). The Dependency Ratio is the proportion of non-working (< 15 or > 65 years) relative to the total population in each census small area unit.

We used the margins command in Stata 13.1 to estimate and interpret adjusted predictions for sub-groups, while controlling for other variables such as time, using computations of average marginal effects. Margins are statistics calculated from predictions of a previously fitted model at fixed values of some covariates and averaging or otherwise over the remaining covariates. In the multi-variable model (Poisson), we adjusted univariate estimates of effect, using the previously described outcome predictor variables. The model parameters were stored; post-estimation intra-model and cross-model hypotheses could thereby be tested.

Statistical significance at $p < 0.05$ was assumed throughout. Stata v.13.1 (Stata Corporation, College Station, TX) statistical software was used for analysis.

Results

Patient demographics (Table 1)

A total of 96,526 episodes in 50,731 unique patients were admitted as medical emergencies from the hospital catchment area over the 15-year study period (2002–2016). These episodes represented all emergency medical admissions, including patients admitted directly into the intensive care unit or high dependency unit respectively. The proportion of males was 48.6%. The median (IQR) length of stay (LOS) was 4.4 (1.8, 8.9) days. The median (IQR) age was 58.7 (38.0, 76.2) years, with the upper 10% boundary at 84.9 years.

Deprivation status was classified by Quintiles (Q1 low–Q5 high) at the level of the District Electoral Division. There were a total of 74 EDs in the catchment area with a population of

Table 1 Characteristics of emergency medical admissions by deprivation status

Factor	Level	Low deprivation	High deprivation	*p* value
N		20,057	42,366	
Gender	Male	10,255 (51.1%)	20,215 (47.7%)	< 0.001
	Female	9802 (48.9%)	22,151 (52.3%)	
Outcome	Alive	18,953 (94.5%)	40,348 (95.2%)	< 0.001
	Died	1104 (5.5%)	2018 (4.8%)	
Age, median (IQR)		65.8 (45.6, 79.5)	65.2 (46.0, 78.1)	< 0.001
Length of stay (days)		5.2 (2.2, 10.2)	5.3 (2.3, 10.0)	0.53
Admission incidence		17.6 (10.6, 28.9)	38.5 (31.2, 43.6)	< 0.001
Acute illness Severity	1	491 (2.7%)	1018 (2.6%)	0.055
	2	1173 (6.4%)	2454 (6.3%)	
	3	2004 (10.9%)	4506 (11.6%)	
	4	2993 (16.3%)	6401 (16.5%)	
	5	3659 (20.0%)	7917 (20.4%)	
	6	7998 (43.7%)	16,469 (42.5%)	
Charlson index	0	9050 (45.2%)	17,446 (41.3%)	< 0.001
	1	5673 (28.3%)	12,646 (29.9%)	
	2	5289 (26.4%)	12,178 (28.8%)	
Disabling disease	0	2090 (10.4%)	4112 (9.7%)	< 0.001
	1	4997 (24.9%)	10,087 (23.8%)	
	2	5819 (29.0%)	12,251 (28.9%)	
	3	4414 (22.0%)	9447 (22.3%)	
	4	2737 (13.6%)	6469 (15.3%)	
Sepsis status	0	15,053 (75.1%)	32,439 (76.6%)	< 0.001
	1	4275 (21.3%)	8459 (20.0%)	
	2	729 (3.6%)	1468 (3.5%)	

LOS length of stay, *MDC* major disease category, *IQR* inter-quartile range

210,443 persons, as per the 2006 Census. The 2006 median population per ED was 2845 (IQR 2020, 3399). These areas were ranked nationally as deprivation quintile I ($n = 13$), quintile II ($n = 0$), quintile III ($n = 5$), quintile IV ($n = 7$) and quintile V ($n = 49$). The demographic characteristics (Table 1) are outlined with a cut point at the Q3/Q4 boundary and tabulated by Acute Illness Severity [24, 25], Charlson Co-Morbidity Index [26], Chronic Disabling Disease Score [27] and Sepsis status [28]. Patients from less deprived areas (Q1–Q3) were on average older at time of admission 66.1 year (46.2, 79.2) compared with the more deprived 64.8 years (45.7, 78.1); they had a higher 30-day in-hospital mortality by episode on average (5.4 vs 4.8%; $p < 0.001$). The admission incidence rate was considerably higher from the more deprived areas—38.5 (95% CI 31.2, 43.6)/1000 population vs. 17.6 (95% CI 10.6, 28.9), $p < 0.001$. The older patients from less disadvantage areas (higher SES) had more Acute Illness Severity, Chronic Debilitating and Respiratory Disease, whereas, more broadly speaking, the Q1/Q3 and Q4/Q5 admitted patients groups appeared similar in terms of Acute Illness Severity, Charlson Co-morbidity, Chronic Disabling Disease and Sepsis rates.

Comparison of census deprivation ranks between SAHRU and POBAL

There are 74 Electoral Divisions within the hospital catchment area; there was poor agreement between the Deprivation Instruments as to the appropriate Quintile Ranks. Based on the 2006 Census, there was agreement on the small area classification in 46% of population areas and for the 2011 comparison the absolute agreement in area classification was only in 42% of population areas. For the 2006 Census, POBAL ranked 42 and 32% in quintiles 1 and 5 respectively; SAHRU ranked the least and most deprived at 18% (Q1) and 66% (Q5) respectively. For the 2011 Census, POBAL ranked 50 and 24% in quintiles 1 and 5 respectively; SAHRU ranked the least and most deprived at 18% (Q1) and 55% (Q5) respectively. The impact of assessment at the small area level appeared to be an upwards ranking bias of POBAL versus SAHRU (towards less deprivation), and this resulted in higher admissions incidences being allocated to lesser deprived areas compared with the SAHRU classification.

Admission and readmission incidence rates (Figs. 1 and 2)

The admission incidence rate was significantly predicted by the area deprivation status, in the multiple variable model adjusted for the other predictive variables of Acute Illness Severity [24, 25], Charlson Co-Morbidity Index [26], Chronic Disabling Disease Score [27] and Sepsis status [28]. For SAHRU, the IRR for deprivation was 1.48 (95% CI 1.47, 1.49) in the 2006 model and 1.47 (95% CI 1.46, 1.48) in the 2011 model. The calculated admission incidence (rate/1000 population) increased from Q1 of 7.8 (95% CI 7.7, 8.0) to Q5 of 37.7 (95% CI 37.4, 38.0) for the 2006 Census data and from Q1 of 8.5 (95% CI 8.3, 8.6) to Q5 of 39.4 (95% CI 39.1, 39.7) for the 2011 census data.

For the 2006 Census, the POBAL multiple variable model adjusted for other predictive variables was predictive but at a lower level than SAHRU with a Deprivation level IRR of 1.28 (95% CI 1.27, 1.28) for the 2006 model and 1.26 (95% CI 1.26, 1.27) for the 2011 model. The calculated admission incidence rates were consistently higher (Fig. 1) than with the SAHRU models; the calculated admission incidence increased from Q1 of 16.6 (95% CI 16.4, 16.9) to Q5 of 44.4 (95% CI 44.0, 44.7) for the 2006 Census data and from Q1 of 17.9 (95% CI 17.6, 18.2) to Q5 of 45.7 (95% CI 45.3, 46.0).

The readmission incidence estimates were similarly higher (Fig. 2) for the POBAL compared with the SAHRU based on the Census deprivation ranks. The model predictions for SAHRU, with incidence rate ratios of 1.69 (95% CI 1.68, 1.71) in the 2006 model and 1.64 (95% CI 1.63, 1.65) in the 2011 model, were higher than those for the POBAL 2006 and 2011 Census estimates of the effect of deprivation. The POBAL model had IRRs for of 1.32 (95% CI 1.32, 1.33) and 1.30 (95% CI 1.29, 1.31) for the 2006 and 2011 periods respectively.

Modelling based on different censuses (2002, 2006 and 2011—Fig. 3)

We do not know the time frame over which environmental or socio-economic factors operate to determine health outcomes, that is, to weigh how long is the risk exposure before the consequence is expressed as the emergency medical admission? If the duration of exposure is decades, for example, then we cannot anticipate that changing Census statistics will be accompanied by coincidental change in admission incidence rates. More remote Census data might therefore provide better prediction than more recent data. We therefore modelled the ability of deprivation status (hospital catchment 74 Electoral Divisions by quintiles of SAHRU classification) for three consecutive censuses, 2002, 2006 and 2011. We adjusted the data for

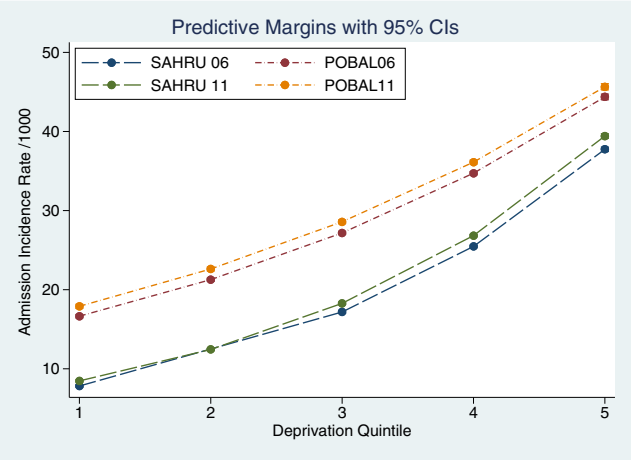

Fig. 1 The hospital admission incidence (rate/1000 population) was strongly influenced by the deprivation status. The SAHRU and POBAL ranks were for catchment small areas (DED) from low Q1 to high Q5 deprivation. The predicted probabilities were derived from the multiple variable truncated Poisson model; the effect is plotted based on the latter prediction. Data was from two censuses in 2006 and 2011. POBAL admission rate incidence rates were consistently higher than SAHRU estimates

Dependency Ratio, Acute Illness Severity Score [24, 25], the Charlson Comorbidity index [26], the Chronic Disabling Score [27] and Sepsis Status [28]. The multivariable model indicated that the hospital emergency medical admission incidence rates were predicted by all three censuses with IRRs of 1.27, 1.28 and 1.22 for the 2002, 2006 and 2011 respectively. The models were different with both 2002 and 2006 superior to 2011 in terms of outcome prediction; there were small differences between 2002 and 2006 ($\chi^2 = 88.2$; $p < 0.01$).

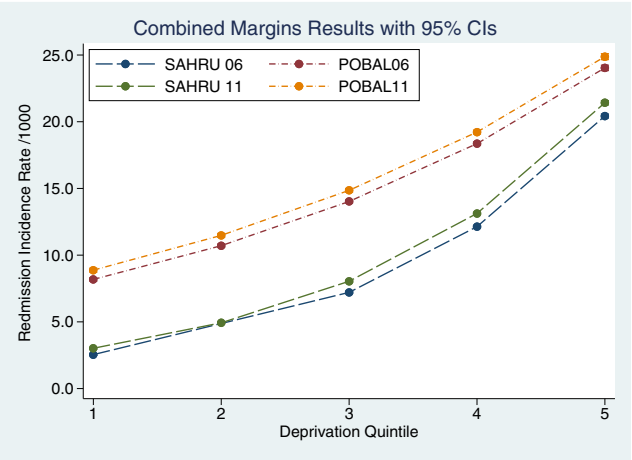

Fig. 2 The hospital readmission incidence (rate/1000 population) was strongly influenced by the deprivation status. The SAHRU and POBAL ranks were for catchment small areas from low Q1 to high Q5 deprivation. Data was from two censuses in 2006 and 2011. Readmission rates were cumulative readmissions for each District Electoral Division/1000 population averaged over 15 years

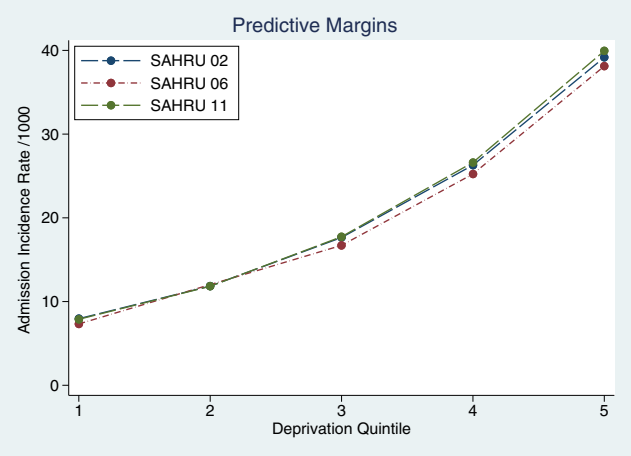

Fig. 3 The model of hospital readmission incidence (rate/1000 population) was compared over three consecutive censuses—2002, 2006 and 2011. The SAHRU ranks were for catchment small areas from low Q1 to high Q5 deprivation. The most consistent and reliable statistical model for the readmission rate incidence was based on the 2002 and 2006 census data

Discussion

Our hospital, St. James' Hospital, is in an area of high deprivation [9]; our experience in working in such an environment and dealing with the impact of environmental and socio-economic conditions on the human condition influences our thinking. We are interested in deprivation in terms of its aggregate community influences rather than at the levels of individual personal disadvantage. We therefore have focused on areas of residence designated as deprived by census-based indicators and directed our healthcare research investigations to determine the extent to which health outcome and healthcare consumption patterns can be explained by the concentration in those areas of people with adverse personal or socio-economic factors [30]. Using the SAHRU Deprivation classification for the District Electoral Division (our traditional Census Small Area), we have demonstrated that, within the hospital catchment area, the emergency hospital admission incidence rate for the affluent approximates to 5–10/1000 population, increasing (essentially as a linear function) to 30–40/1000 for deprived areas [5, 31, 32]. The rates of emergency medical admissions at our institution, when considered in absolute terms, were in line with those for the UK; with such a low incidence rate (absolute rate of 1.5–1.7% of population will have an emergency medical admission per annum) [33], the unit area of calculation has to be of a reasonable size; within the catchment area, there are 74 District Electoral Divisions (DEDs) with a median population per ED of 2845 (IQR 2020, 3399). This sample size appeared adequate to allow incidence rate calculations to permit the correlation of deprivation on acute 30-day acute hospital mortality [10], admission and readmission rate incidences [11] and hospital costs [12] to be determined. Of course, being a single hospital, we have to average our admission and readmission rate incidence over time, as our population represents only 5% approximately of that in the State. This work attempts to outline some of the unanticipated consequences that may follow when there is a fundamental change in the construct of the deprivation instrument.

Deprivation instruments have other utilities apart from the study of population healthcare statistics. The limitation of the classical deprivation model is that it is reductionist using a factor analytical approach to reduce a larger number of socio-economic or environmental indicators to a smaller number of underlying dimensions, factors or components. However, to capture the richness, diversity and complexity of a society construct requires a different approach as outlined elegantly by Haase and Pratschke [17]. Should one wish to move towards defining deprivation at an even more granular level (street or even individual level), as particularly where a census-based deprivation index is used as a proxy for individual-level social position, then one needs small areas (SAs) to be standardised in size as in POBAL—with this methodology, there are a minimum of 50 households and a mean of just under 100 per small area. Thus, unlike the classical method, where there are a limited number of dimensions that have been defined by data-driven techniques, the multi-dimensional model develops an a priori conceptualisation of the perceived relevance of such dimensions for different applications. While this approach has considerable merit, a perusal of our catchment area mapped by this technique shows a complex mosaic of constructs, with pockets of affluence colloquially termed 'gentrification'. Over time, this reflects new apartment developments as urban regeneration impacts on the inner city. However, the theme prevailing in our publications has been the 'broad paint brush' of 74 Electoral Divisions, with 49 being in the 4th and 5th quintiles (lowest SES) of the SAHRU and the stable relationship to the hospital emergency medical admission rates.

For health research purposes, any classification of deprivation has to be robust, accurate and stable. Ideally, it should demonstrate a linear dose–response relationship, where increasing measures of deprivation have a healthcare outcome consequence—increased admission and readmission rates. An important caveat to the ability of any model to behave in this manner is the fact the introduction into a locale of health protecting entities (such as recreational facilities) or health subversive entities (such as fast food outlets and licenced alcohol premises) may distort the relationship. All other things being equal, it is likely that the socio-economic and environment factors influence healthcare outcome consequence over an extended period (perhaps decades), so changing the classification of an Electoral Division is unlikely to be immediately reflected in an

improvement in healthcare outcomes—at least not until the pool of accumulated risk has been expressed as communities age. Additionally, should one wish to adjust hospital statistics for deprivation status, as in the case of hospital mortality comparisons, then the fitness for purpose of the specific instrument as a healthcare quality indicator needs to be critically evaluated.

In the comparison of SAHRU and POBAL, it is clear that POBAL estimates at the District Electoral Division level consistently classified areas at a higher level of SES; the transfer of classification from more to less deprived resulted in the inflation and compression of the calculated admission and readmission incidence rates. Based on these data, one can immediately identify a problem where the multi-dimensional deprivation metric (in an improving locality ranked higher in SES terms) is no longer in agreement with the rate of clinical presentations and admissions—unlike large population-based deprivation indices. At the very least, it is important that one is aware of this phenomenon. Both methods to estimate socio-economic status have inherent benefits, and one must consider the nature of the research, or service development, question in hand when assessing whether a more or less granular view of deprivation is required. Interestingly, Beeknoo and Jones [34, 35] have described a blended approach that adjusts small area deprivation data to reflect the status of the larger super output area and that this has benefits when describing emergency department, admission and critical care utilisation rates. Finally, there is another dimension to consider. The composition of an area is not stable over time, and this is relevant as there is no clarity in relation to the time frame over which societal changes exert their influence on health outcomes. Increases in the cost of property can rapidly displace the younger cohort of a population and replace them with those from a higher income category. The extent of social integration can be variable, and the influence of new arrivals can distort summary metrics in an area. This phenomenon, gentrification, must be considered when following patients over time [36, 37]. The available evidence suggests that the societal consequences are complex but not that migration of the local poor population might be on a scale to influence overall health statistics [38]; consequently, there may be disparity between the improving metrics suggested by a multi-dimensional deprivation model when set in the context of the numbers of hospital emergency presentations and admissions. These of course will reflect more remote socio-economic circumstances that incubated ill-health as revealed by the current level of clinical presentations. To better inform health planning, it might be useful for future censuses to expand the number of health questions it contains and consider capturing data in relation to primary and secondary care utilisation. This will assist us in discriminating the differential effect of older versus younger and less versus more affluent citizens in a defined population area.

Conclusions

Deprivation influences hospital incidence rates for emergency medical admissions and readmissions. Instruments focusing at the very small area (individual or street level) have a utility but appear inferior in terms of representing the population risk which seems better approximated at a larger scale. This may be particularly relevant over time if there is a methodology shift in assessing the deprivation burden in a small area.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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