The Impact of Socio-Demographic and Clinical Factors on Acute Medical Service Utilisation

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By

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Declaration

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Abbreviations

SES	Socio-economic Status
AMU	Acute Medical Unit
ArcGIS	Arc Geographical Information System
CDM	Chronic Disease Management Programme
CI	Confidence Interval
CSO	Central Statistics Office
CT	Computed Tomography
DNACPR	Do Not Attempt Cardiopulmonary Resuscitation
ED	Emergency Department
EWS	Early Warning Score
FEV1	Fixed Expiratory Volume in one second
GP	General Practitioner
HIPE	Hospital in-Patient Enquiry
HSE	Health Service Executive
ICD	International Classification of Diseases
IQR	Inter-Quartile Range
IRR	Incidence Rate Ratios
LA	Local Authority
LOS	Length of Stay
MDRD	Modification of Diet in Renal Disease
MDT	Multidisciplinary Team
MRI	Magnetic Resonance Imaging
NCEPOD	National Confidential Enquiry into Patient Outcomes and Death
NHS	National Health Service
NICE	National Institute for Clinical Excellence
NNT	Number Needed to Treat
OR	Odds Ratio
PAS	Patient Administration System
PCA	Principal Components Analysis
POBAL HP	POBAL Haase Pratschke Deprivation Index
RCP	Royal College of Physicians
RRR	Relative Risk Reduction
SA	Small Area
SAHRU	Small Areas Health Research Unit
SAPS	Small Area population Statistics
SD	Standard Deviation
SNOMED	Systematised Nomenclature of Medicine
TOC	Transfer of Care
TPR	Temperature, Pulse and Respiration Chart
UE	Unemployment

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Summary

Socio-economic status impacts health throughout the lifecycle. It does this by affecting income, accommodation, access to education and skills, and access to healthcare. This mediates the phenotypic expression of disease and the trajectory of disease progression. When planning services at local, regional and national levels, it is important to account for the potential effect of inequality.

The work for this thesis was completed in a busy urban hospital with a catchment area of 250,000 people spread across 74 electoral districts. There were 106,586 episodes of care evaluated from the period 2002-2016. Aggregated, anonymised, routinely collected clinical and administrative data was used to classify patients according to major disease category, acute illness severity, co-morbidity score, disability status, sepsis status, and electoral division of residence.

Given that admission and readmission rates to hospitals are count statistics, Poisson regression modelling was undertaken to examine the relationships between socio-economic status and multi-morbidity, and to compare the relative impact of the SAHRU and POBAL HP deprivation indices in terms of explaining the effect of electoral divisional social class on hospital admission and readmission rates.

The analysis of the socio-economic status and multi-morbidity indicated that admissions from the low socio-economic group cohort were a decade younger (62.6 years versus 71.4 years) at the time of presentation. The number of co-morbidities was equivalent between the two groups, but the disadvantaged were more likely to have a respiratory diagnosis or diabetes.

There was poor agreement between the SAHRU and POBAL HP Deprivation instruments, with an overall classification agreement of 46% for data derived from the 2006 census and 42% for the 2011 census. The SAHRU deprivation instrument classified 66% and 55% of the subjects studied into the highest deprivation quintile for 2006 and 2011, respectively. In contrast, POBAL HP mapped 32% and 24% into the highest deprivation quintile for 2006 and 2011, respectively. The admission incidence rate was significantly predicted by the area deprivation status in the multiple variable models adjusted for the other predictive variables of acute illness severity, chronic disabling disease score, Charlson co-morbidity index and sepsis status. Utilising SAHRU deprivation rankings, the Poisson Regression returned an incremental rate ratio for deprivation of 1.48 (95% Confidence interval 1.47, 1.49) using 2006 census data and an IRR of 1.47 (95% confidence interval 1,46,1.48) using 2011 data. Modelling with POBAL HP Deprivation index data resulted in an IRR of 1.28 (95% Confidence interval 1.27,1.28) for the census 2006 and an IRR of 1.26 (95% Confidence interval 1.25,1.26) using 2011 data. The same relationship was shown when readmission rates were examined.

Deprivation influences incidence rates for hospital admission and readmission. The classical SAHRU deprivation instrument seems to approximate population risk more powerfully. Earlier census data model are more powerful, suggesting a long latency between social circumstances and the ultimate expression of acute emergency hospital admission

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Chapter 1 . **Introduction**

1.1. Acute Medicine

Acute medicine is best defined as that part of hospital medicine concerned with the immediate and early specialist management of adult patients suffering from a wide range of medical conditions requiring urgent or emergency care (Langlands et al., 2009).

The Acute Medical Unit (AMU) is as much a philosophy of care as it is a physical entity. Prior to the move towards AMUs, it was not uncommon for patients to be admitted and dispersed widely around the hospital with little regard for the coordination of investigations or therapy. A further criticism related to the relative ratio of responsibility placed on the shoulders of junior doctors in training. A body of evidence began to emerge indicating that the consequences of the inefficiencies described resulted in longer hospital stays (Liew et al., 2003) and an increase in direct patient risks such as medical error, complications and avoidable death (Sprivulis et al., 2006). Thus, Acute Medicine developed in the United Kingdom because of changes in the demographic and clinical environment. Specifically, the recognition that admission of acutely unwell medical patients represented the major source of work for most hospitals and the drive to improve clinical governance standards were important. In addition, the medical complexity of an ageing population and the shift towards consultant-led services proved pivotal, as was an increase in bed occupancy rates to over 85% (Capewell, 1996).

The significant growth of acute medicine in the United Kingdom was captured in a Royal College of Physicians census that revealed a 63% increase in the number of Consultants in Acute Medicine between 2002 and 2007 while also highlighting that 92% of hospitals were admitting sick medical patients to an AMU (RCP, 2008).

This has not been a uniquely British phenomenon. Acute Medical units have been established in Australia and Ireland, and the Hospitalist movement has been gaining in popularity in North America (Peterson, 2009). The feature unifying the AMU and Hospitalist approach is the recognition that traditional models of hospital care were not patient-centred, delivered poor outcomes and offered bad value for money. There was also a recognition that standardising aspects of medical management can improve the outcome of many conditions, such as stroke (Indredavik et al., 1991) and myocardial infarction (Rogers et al., 2007).

1.1.1. Key features of the AMU

There are a variety of synonyms for the AMU. These include the acute medical admissions unit; the medical assessment unit; the acute assessment unit and rapid assessment medical units among others. Irrespective of the name, an AMU is best defined operationally. (Bell et al., 2008) defined the AMU as "medical wards staffed and equipped to deal exclusively with acute medical patients transferred from either the emergency department or community for rapid specialist medical and multidisciplinary assessment and treatment". Central to this was the development of medical early warning scores based on easily accessed clinical data (Subbe et al., 2001, Silke et al., 2010, Kellett and Deane, 2009). Typically, the unit would have a maximum length of stay (72 h in most cases) and benefit from a convenient location with respect to diagnostic services and often avail of priority service level agreements to deliver key critical path investigations in a timely manner. Another key feature is the presence of consultants with an interest in acute medicine.

The AMU acts as a fulcrum for acute medical care. Those patients who can be stabilised, treated, and discharged are dealt with efficiently. If it emerges that the patient is likely to require a longer hospital stay, then a prompt and appropriate handoff to the speciality in question is merited. Key to this is close co-operation and mutual respect between the complementary specialties. Most AMUs are unlikely to accept patients where there is haemodynamic instability requiring intensive care level monitoring; patients where there are defined special needs such as stroke or acute oncological emergencies; frail elderly with multiple co-morbidities requiring specialist elderly care; and those patients more in need of respite or residential care.

The objectives of the AMU can be summarized as follows (Scott et al., 2009)

-Rapid and comprehensive multidisciplinary assessment of acutely ill medical patients led by appropriately trained acute care physicians

-Early consultant review of admitted patients and referral as appropriate to specialist teams

-Rapid turnaround in pathology, radiology, and other investigative services

-Improved access to Geriatric assessment, community health nurse review and other clinical management resources

-Reduction in waiting times for patients in emergency departments to access hospital beds

-Elimination of need to board patients in non-home wards

-Develop care bundles to standardize the management of acutely ill patients

-Optimize bed management by using care pathways that obviate the need for admission to hospital

-Facilitate clinical and health service research into care of acutely ill medical patients

-Reduction of staff fatigue by improved rosters and the use of shifts.

These objectives are derived from a number of key reports and recommendations including the Acute Medicine Taskforce (RCP, 2007), the National Confidential enquiry into Patient outcomes and death (NCEPOD,

2007) and the National Institute for Health and Clinical Excellence (NICE, 2007). (Ward et al., 2009) report on an audit to evaluate the role of the structure and organization of acute medical care on patient outcomes. Twenty-seven of 39 trusts requested to complete the survey responded. Of those who responded all but one had an AMU. All 26 AMUs had a designated lead consultant. Only two trusts did not have a written operational policy. Twenty-one of the 26 who responded used an early warning score at the point of entry to care. Only 10 trusts reported that other clinical duties were cancelled for consultants on the day of clinical take. It is also worth noting that 10 of the trusts reported that consultants did a minimum of twice daily ward rounds on the AMU seven days per week. 'Consultant of the day' remained the most common working practice. The Acute Medicine Taskforce described an 'ideal' MAU configuration (see figure 1).

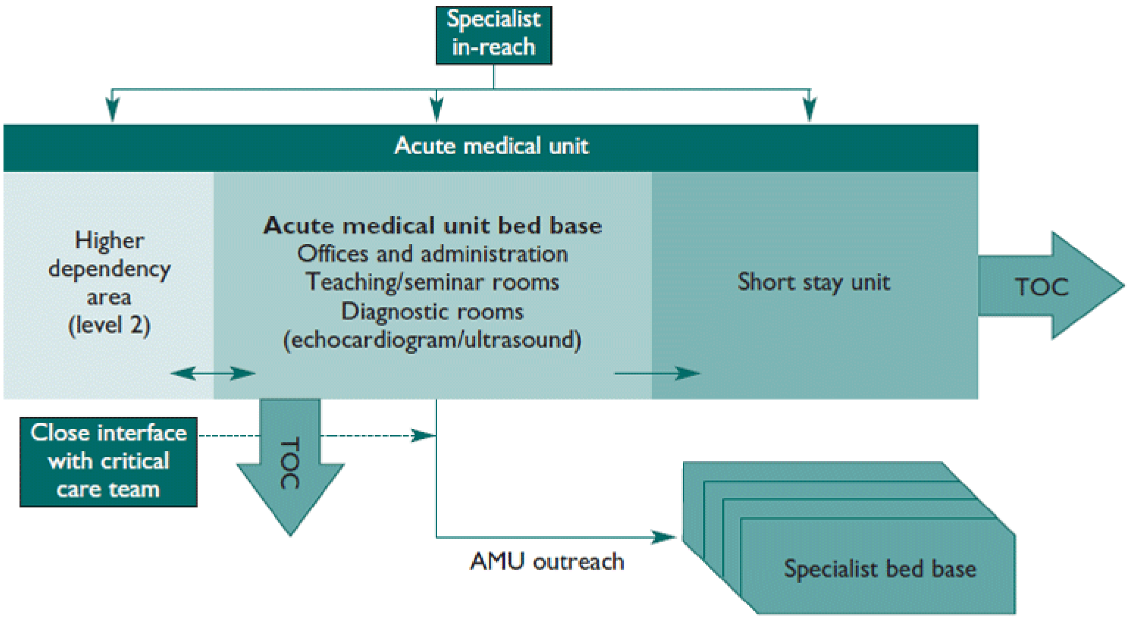


Figure 1.1: Ideal Acute Medical Unit Configuration.

Interactions and Transfer of Care (TOC) is outlined along with Specialist In-reach (consults to aid early discharge or identify patients for TOC to Specialist bed base) and AMU outreach to support urgent care for the hospital. After Report of the Acute Medicine Taskforce (RCP, 2007).

The Royal College of Physicians in Edinburgh UK consensus statement detail the following quality of care and performance indicators (Langlands et al., 2009).

Quality of care indicators

1. ***Patients should be assessed by a competent decision maker within 30 minutes of in-hospital referral to an acute medical team from the emergency department or on arrival at the acute medical unit if directly referred***

2. ***A treatment and investigation plan should be formulated and instigated within 60 minutes of arrival***

3. ***Patients to be seen and management plan established within 12 hours, but preferably sooner, by the admitting consultant physician***

4. ***Patients to have an early warning score system recorded at point of entry to care***

5. ***Patients to have regular early warning score undertaken, preferably as part of their routine physiological recording (TPR chart) with locally defined response systems***

6. ***Single sex accommodation to be provided except within monitored areas (i.e., when the severity of the condition outweighs this)***

7. ***Regular monitoring of key performance indicators in acute care***

8. ***The initial assessment, investigation and treatment of all patients presenting in an unscheduled manner should be consistent with the 'four-hour standard' regardless of their place of treatment (ED, AMU or joint early care unit)***

9. ***NHS boards have policies and guidance in place to ensure the timely undertaking of investigations appropriate to unscheduled care patients***

<u>Performance indicators</u>

1. Mortality rates

a. Within 48 h of admission

b. Hospital mortality rates

c. Weekend versus midweek mortality rates

d. Day versus 'out of hours' (0800–1900 vs 1900–0800)

2. Direct discharge rates monitored within 25 or 48 hours of admission.

3. Re-admission rates within 7 days of discharge

4. Intermittent audit of tracker conditions

5. Patient experience

A number of factors have been identified that influence the operation, and success or otherwise, of an AMU (Scott et al., 2009). These are summarized as:

Success factors

1. Governance structure that includes medical, nursing, and allied health disciplines
2. Rigorous business rules around patient entry and clearly defined processes of admission and discharge of eligible patients
3. Consultant leadership and supportive hospital management
4. Group of general physicians willing to take part in an acute roster
5. Dedicated multidisciplinary support
6. Close to Emergency Department/good working relationship
7. Twice daily multidisciplinary ward rounds
8. Prioritized access to investigative facilities
9. Implementation of standardised evidence-based protocols
10. Co-operation of speciality colleagues in early review and acceptance of patients referred from AMU
11. Access to early clinic appointments and other post discharge support services
12. Regular evaluation and feedback of quality indicators
13. Clerical assistance and strong information technology support

Barriers

1. Difficulty recruiting nurses and allied health staff with appropriate levels of acute assessment skills

2. Inadequate nurse patient ratios (< 1:5)

3. Exit block from AMU

4. Non-AMU gaining access to unit beds; especially out of hours due to general bed pressures.

5. Sequestering of beds on basis of infection control potential

6. Gerrymandering of MDT resource for patients who have a longer-term rehabilitation outlook

7. Lack of co-operation from speciality colleagues with respect to low acuity/high complexity cases

8. Risk of consultant to high pace/high acuity/high stress

The future success of AMU's will lean into the emerging field of implementation science. (Green et al., 2017) investigated the factors that supported the successful deployment of care bundles in the Acute Medical setting. Resource availability (including training and capacity development) was the first key determinant. Secondly, it is vital to engender a sense amongst the key stakeholders that the new initiatives are sustainable. This maps to the third success factor, senior leaders must actively engage in the early adoption phase and maintain their support into the enduring control phase of a change project. The final success factor is building in tangible practitioner incentives for those who engage in change- this may take the shape of direct funding or improved staffing ratios.

1.1.2. <u>Evidence of benefit of AMU care</u>

There are substantial difficulties in making overarching claims of benefit for AMUs. These derive from the heterogeneity of operational policy, geographical differences in health care delivery and the limited data that exists to date.

Nonetheless, there are several impressive reports in the literature outlining the efficacy of AMUs. A single centre reported a 44% relative reduction in 30-day in-patient mortality over the first 5 years of operation of their AMU (Rooney et al., 2008). This prospective study of over 33,000 patients presenting to a university teaching hospital in Dublin showed a mortality reduction from 12.6% in 2002 to 7% in 2006 ($p < 0.001$), yielding a number needed to treat (NNT) of 18 people. By 2010 the relative risk reduction had increased to 55%, with a NNT of 11.9 (Fig. 1). One can calculate the lives saved annually, by taking the mortality in 2002 as the expected mortality; these then are the absolute mortality reduction as a percentage of the total number of unique patients admitted each year (Fig. 2). What is otherwise not apparent might be inferred from this graph — the benefits of a system change may not be immediate but appear to accumulate disproportionately over time, as if there were multiplicative effects resulting from system change.

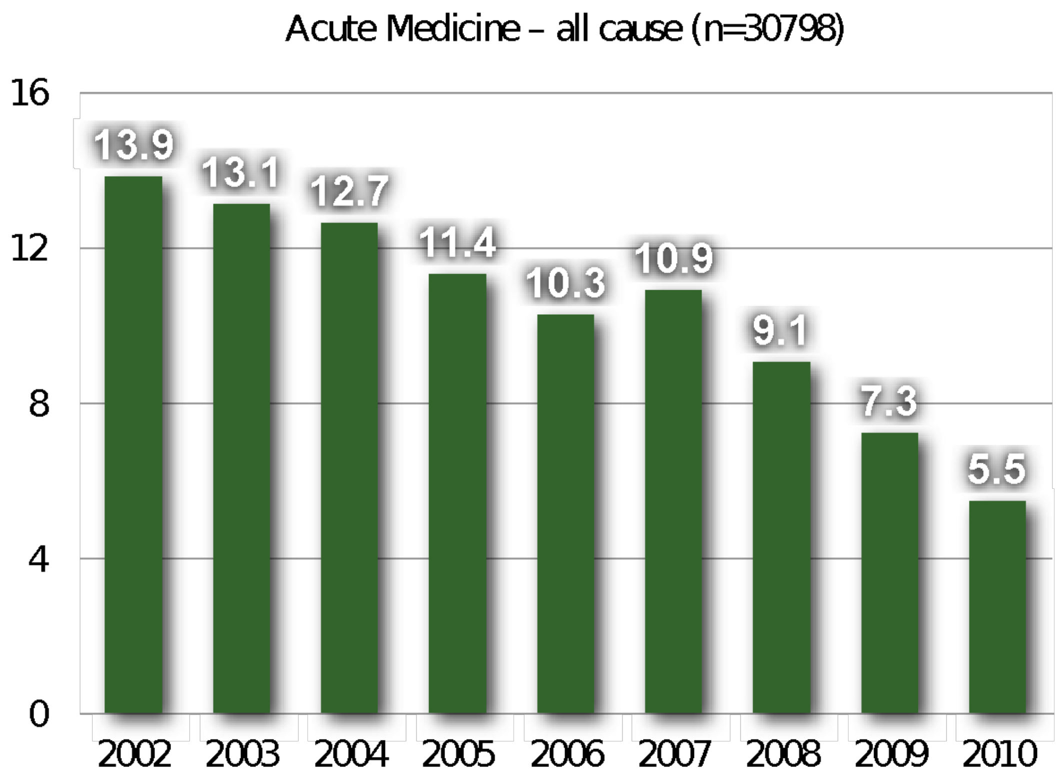


Figure 1.2: Reduction in Acute Hospital Mortality.

The hospital mortality illustrated is for all emergency medical admissions to St James' Hospital from 2002 to 2010 inclusive. The relative risk reduction (RRR) was 55% with numbers to treat (NNT) of 11.9.

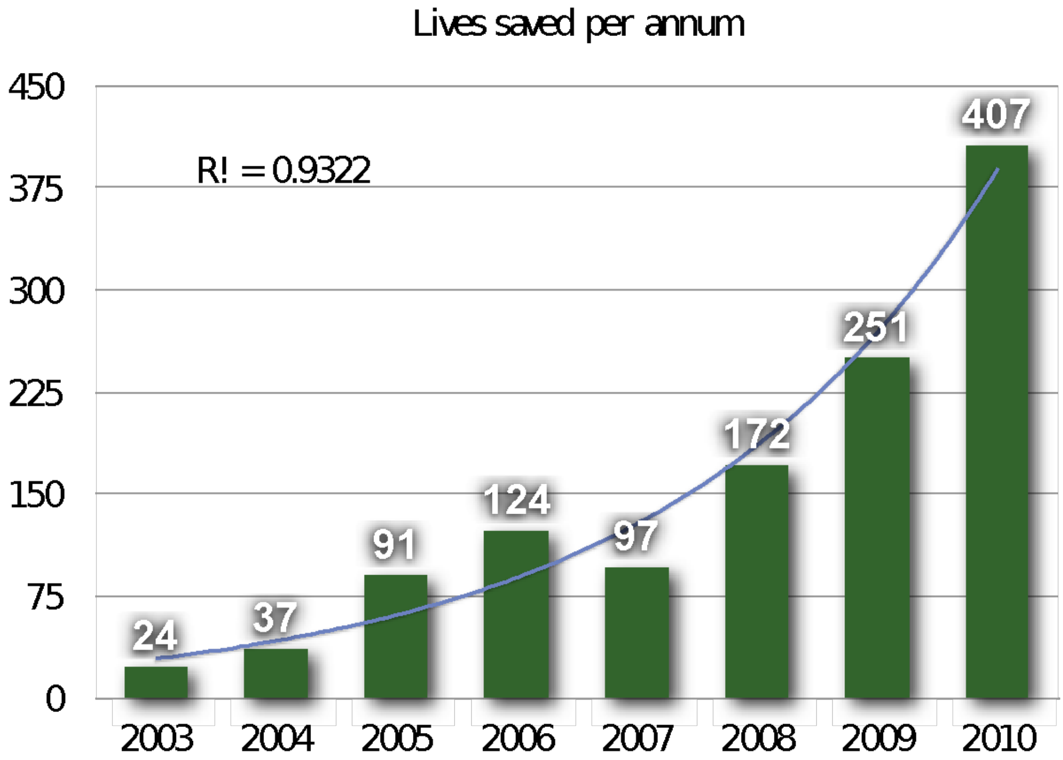


Figure 1.3: Lives saved after reconfiguration of acute care.

The annual lives saved have been calculated from the numbers of patients admitted each year and the observed mortality in each year (observed) versus the mortality in 2002 (expected).

Interestingly the beneficial effect began to emerge after one year of operation and continued despite a 14% increase in annual workload and an incremental increase in co-morbidity burden and acute illness severity at the time of presentation. The benefit of the AMU was seen in the over 70s as well as the under 70s, but a significant excess mortality risk was seen in the older group — with illness severity playing a more important role than chronic disease burden in this regard (Byrne et al., 2010). As well as defining an operational benefit in terms of outcome, length of stay reductions from 6 days (95% CI 3–15) to 5 days (95% CI 2–12) ($p < 0.001$) were reported (Moloney et al., 2005). Studies have also looked at the emergency department/AMU interface. In one centre, the establishment of the AMU was followed by a 30% reduction in the number of patients required to wait more than four hours for a hospital bed (Moloney et al., 2005). Another interesting marker was a decrease in the number of patients in the Emergency Department awaiting access to a bed on the ward from 14 in 2002 to 2 in 2006 (p <

0.001) (Rooney et al., 2008). This is important when one considers that the effect of waiting in an Emergency Department and subsequent 30-day in-patient mortality may increase from 5% at a wait time of less than 2.5 hours to > 17% at a wait time of over 9 hours ($p < 0.001$) (Plunkett et al., 2011). Overall, in crude terms, a university hospital with 700 beds estimated that their AMU resulted in saving of over 4000 bed days per annum with a putative cost saving of €1.7 million accruing (Moloney et al., 2007).

(Moore et al., 2006) from the Royal Liverpool University Hospital demonstrated a reduction in all-cause hospital mortality from 7.2 to 5.9% ($p = 0.04$) following the establishment of their AMU in the period 1995–2003. Furthermore, they described a 27% reduction in mortality for the under 65-year age group from 3.1 to 1.8% ($p = 0.02$). The flow of patients towards their appropriate speciality also improved significantly in this period, with an increase from 27% to 56% being so described. In addition, the mean length of stay reduced from 9.3 to 8.8 days, but this failed to reach statistical significance.

Chelsea and Westminster Hospital (St Noble et al., 2008) have reported significant improvements in direct home discharges with rates at 24 hours going from 21 to 29% ($p < 0.005$) and from 31 to 40% ($p = 0.004$) at 48 hours. This is reflected in the reduced length of stay seen in this institution falling from 9.3 to 7.8 days ($p = 0.03$) after 4 months of AMU operation. The Royal Bournemouth hospital also described improved direct discharge rates to 32% by the third year of its operation. An additional advantage was the reduction in medical outlier bed days by 16% (Armitage and Raza, 2002).

There are questions relating to the optimum staffing pattern of the AMU. A particular focus has been pattern of the consultant attendance and the effect on patient outcomes. This question was addressed by (Bell et al., 2013) using routinely collected administrative data from 1.3 million episodes of care across 91 hospitals in the UK. Their analysis controlled for co-morbidity and deprivation. They compared the traditional 'Physician-of-the-day' model with programmed continuous consultant presence on the MAU for more than 4 hours per day and a more intensive pattern of attendance that involved working on the AMU for 2-3 consecutive days and rounding twice per day. Statistically significant (but unquantified) benefits were described for adjusted case fatality rate and readmission rate. The intensive pattern of attendance also positively impacted the adjusted case fatality rate of those admitted on weekends versus weekdays. Interestingly, there was no dividend recorded mean length of stay. This contrasts with the impact of consultant presence described by (McNeill et al., 2009), where, in a study of approximately 3,000 episodes of care, the effect of weekdays (Monday-Friday; 0900-1700) was evaluated. Here, the mean length of stay reduced from 9.06 days to 7.72 days (p=0.048) in the intervention group. In addition, the proportion of patients discharged 'the same day' increased from 23% to 32.2%.

An interesting study by (Glynn et al., 2011) looked at the characteristics of patients who are re-admitted to the hospital. The study was based at St. James' Hospital in Dublin, and it demonstrated that over an extended period of time, 27% of the patient cohort had been admitted at least once. The trend for readmissions increased over time, and the authors suggested that efforts to avoid readmissions would perhaps be best focused on efforts to modify underlying chronic disease.

An emerging trend in acute medicine is the adoption of the ambulatory care model. An early study of the efficacy of Rapid Access Medical Clinics (Jamdar et al., 2010) demonstrated a statistically significant improvement in same-day discharge rate from 17% to 25% in their institution. A similar quantum of admission diversion was demonstrated in Bournemouth, where a consultant-led service diverted 30% of over 7,000 presentations from admission over a 3-year period (Khadjooi et al., 2009). (McCallum et al., 2010) reflect on the Directory of Ambulatory Care that was developed by the Society for Acute Medicine and the NHS Institute for Innovation and Improvement. They surveyed over 130 AMUs and discovered that 79% of respondents had some manner of ambulatory care. However, the clinical cover was ad-hoc and poorly coordinated. This has changed over the last decade and it is now a vital component of the emergency care offering in the NHS (Hamad and Connolly, 2018). This transformation has leveraged off the deployment of technology such as High Sensitivity Troponin measurement and low molecular weight heparin treatments, informed by risk stratification tools that act as a gateway to the ambulatory model (Ala et al., 2012, Thompson and Wennike, 2015). A systematic review has shown that for low-risk patients, alternative management strategies to inpatient care can achieve comparable outcomes at lower costs across a range of conditions (Conley et al., 2016).

A major criticism levelled at AMU research is that there is a dearth of randomised controlled trials. In addition, there is potential for publication bias as probably less than 10% of all available AMUs have reported outcomes. The development of local AMU is cognizant of local workforce challenges, the prevailing clinical and demographic landscape, and is sensitive to those established services that are safe, effective, and delivering for the community. Thus, there is no commonality to the design of 'the' acute medical unit, and it may not be reasonable to anticipate that all systems will produce the same beneficial outcomes, despite this proliferation of models. There have been three high-quality reports setting out how deploying multiple interventions in their AMUs have delivered. The earliest was published by (Wald et al., 2001). The bundle of measures implemented by this group included appointing a senior resident trainee into their AMU, GP referral bypassing the ED, establishing a rule that all consultant post-call ward rounds should complete by 1000, and that a second daily round is completed by the senior resident at 1600; daily MDT meetings were commenced and support services were encouraged to give AMU priority; an onsite pharmacy was also installed with 24-hour access to commonly used medications; finally- the Bed Manager was relocated into the AMU. This set of measures successfully re-profiled the attendance pattern of patients- the proportion of GP-referred patients seen in ED fell from 54% to 20% whilst reciprocally increasing from 46% to 80% in the AMU. The percentage of patients who required a length of stay of more than 2-days fell from 79% to 37%. Same day discharge rate increased from 11% to 21%.

(Epstein et al., 2007) describe an observational study of 250 patients before and after implementing a suite of interventions. The interventions comprised expedited ward discharges by clinical staff and bed managers, active management of patients over the weekend period by the on-call service, designated consultant of the week for acute medicine, preferential weekday access to diagnostics such as CT/ MRI/ endoscopy/ echocardiography, day-of-referral specialist consultation and enhanced pharmacy support. The outcomes of the intervention included: a doubling, to 80%, of ED referrals directly to the AMU in the intervention group; the proportion of patients leaving the AMU within 48 hours also doubled to 90% after the change with AMU LOS reducing from 3.9 days to 1.8 days; 100% of patients seen by a consultant within 12 hours of arrival; the number of weekend discharges increased from 2 to 25; finally the intervention also helped the hospital reduce the proportion of patients breaching the 4-hour ED rule from 19% to 14%. In another quality improvement study, (Beckett et al., 2013) assessed the impact of the following: a bundle of measures around early score including a) their introduction into the emergency department, b) their routine use in nursing handover, c) systematic staff training in EWS, d) introduction of "recognise and respond" stickers; creation of a weekly safety MDT; formalised monthly Acute Medicine Morbidity and Mortality meetings; a suite of measures around recognising and managing dying patients including a DNACPR policy and palliative care referral; structured twice daily ward rounds and the creation of a visible safety "Dashboard" that all staff could see. The interventions yielded the following results a 73% reduction in emergency calls to the AMU for deteriorating patients, a 71% reduction in the number of cardiac arrest calls (2.8/ 1000 admissions to 0.8 /1000). Also, the 30-day mortality rate for patients admitted to the AMU reduced from 6.3% to 4.8%.

It is noteworthy that, in parallel, the data around Hospitalist care in North America has been shown to reduce the length of stay, mortality, readmission rates and result in a lower cost per admission (Auerbach et al., 2002, Carek et al., 2008, Davis et al., 2000). The explanations for this range from suggesting that the hospitalist is less distracted by competing interests such as outpatient clinics, to an experience theory — i.e., the hospitalist develops expertise in acute medicine over time due to the constant exposure and honing of skills.

1.1.3. **Conclusions**

Acute Medicine and Acute Medical Units are evolving to deal with a number of key internal and external factors that make the process of medical care challenging. There is sound evidence to demonstrate that they yield benefit, or more conservatively, at least cause no harm. There is an opportunity for patient care to continue to improve as processes become standardised and care pathways become codified. We expect that the Acute Medicine/Hospitalist movement will expand and become more common in the international arena. This evolution will occur as part of an evidence base re-design of comprehensive unscheduled care services as envisioned by the Acute Medicine Taskforce (RCP, 2007)- see figure 4.

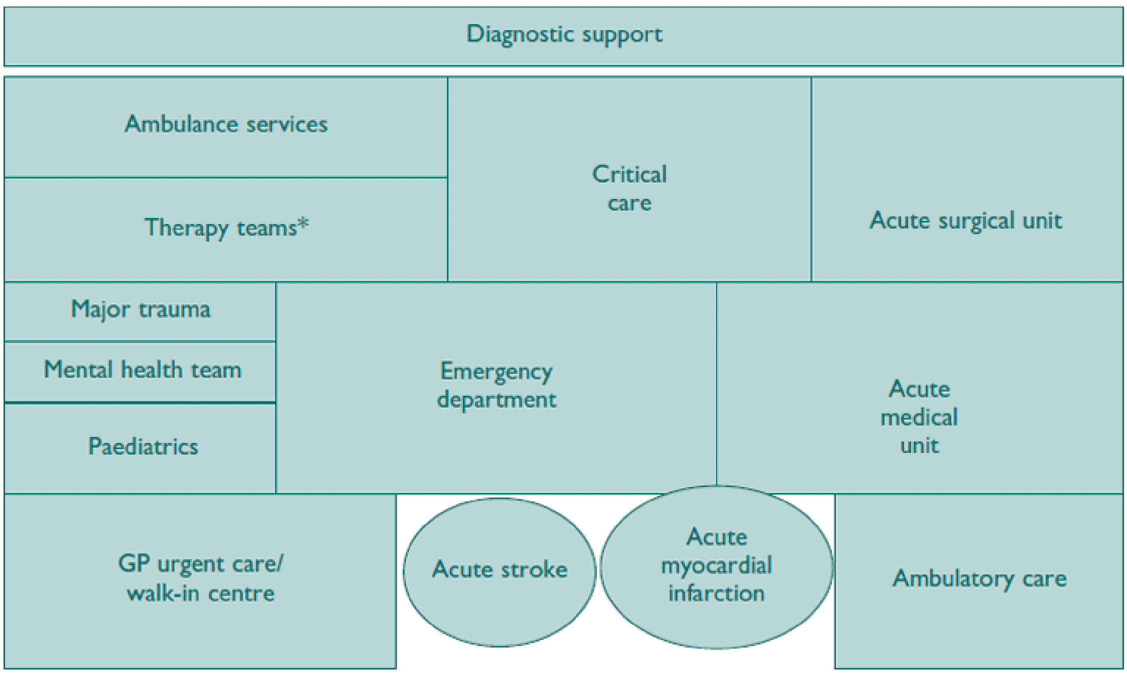


Figure 1.4: Ideal Configuration of Unscheduled Care services in a large hospital.

****Therapy Teams include Physiotherapy, Occupational Therapy, Mental Health & Specialist multidisciplinary teams.***

1.2. Socio-economic Status and Health

1.2.1. **Social epidemiology**

Social Epidemiology is the study of the relationship between social factors and disease in populations. The term “social factors” can be broadly construed given the manner in which human lives are lived. However the conceptualisation as applied to social determinants of disease often collapses into the three primary axes of contemporary social stratification - race, gender and class (Rothman, 2002). In turn, each of these dimensions acts through complex pathways to determine exposures, physical constitution and human behaviour. The concept of “class” is best examined through the lens of socio-economic status, which is operationalised under the headings of education, occupation and income. It is worth noting that this framework links back to the ideas of Max Weber, who proposed that differential societal position is based on the 3-dimensions of class, status, and power. Class has an economic basis, implies ownership of resources and is reflected by measures of income (Smelser and Lipset, 1966). Status denotes prestige in the community and is associated with “access to life chances”. Status can be described in terms of family background, lifestyle, and social networks. Finally, power reflects one’s ability to “get things done” and relates to a political context. The dominant view in sociology is that occupation is the best single reliable indicator of relative standing in industrial societies as it reflects “prestige” conceptualised as part of Weber’s status domain- this flows from the level of esteem the public have for the role, and secondly, it connotes socio-economic position as per Weber’s class domain and reflects judgements made educational requirements and monetary pay-offs that are associated with the position (Haug, 1977).

1.2.2. <u>Mechanisms by which Socio-economic Status may influence health and disease</u>

It is well-recognised that social determinants act as risk factors for many diseases and behaviours that materially affect health (Marmot et al., 2008, Di Cesare et al., 2013). The relationship is complex, can be observed across the social gradient (Singh-Manoux et al., 2003) and cannot be exclusively explained by health behaviours (Stringhini et al., 2011). This particular phenomenon was the subject of a special United Nations meeting in 2011(Beaglehole et al., 2012). A European study reported on the relative inequality across 22 countries and showed that there is variation within and between countries with respect to the impact of socio-economic parameters on mortality- see figure 5 (Mackenbach et al., 2008).

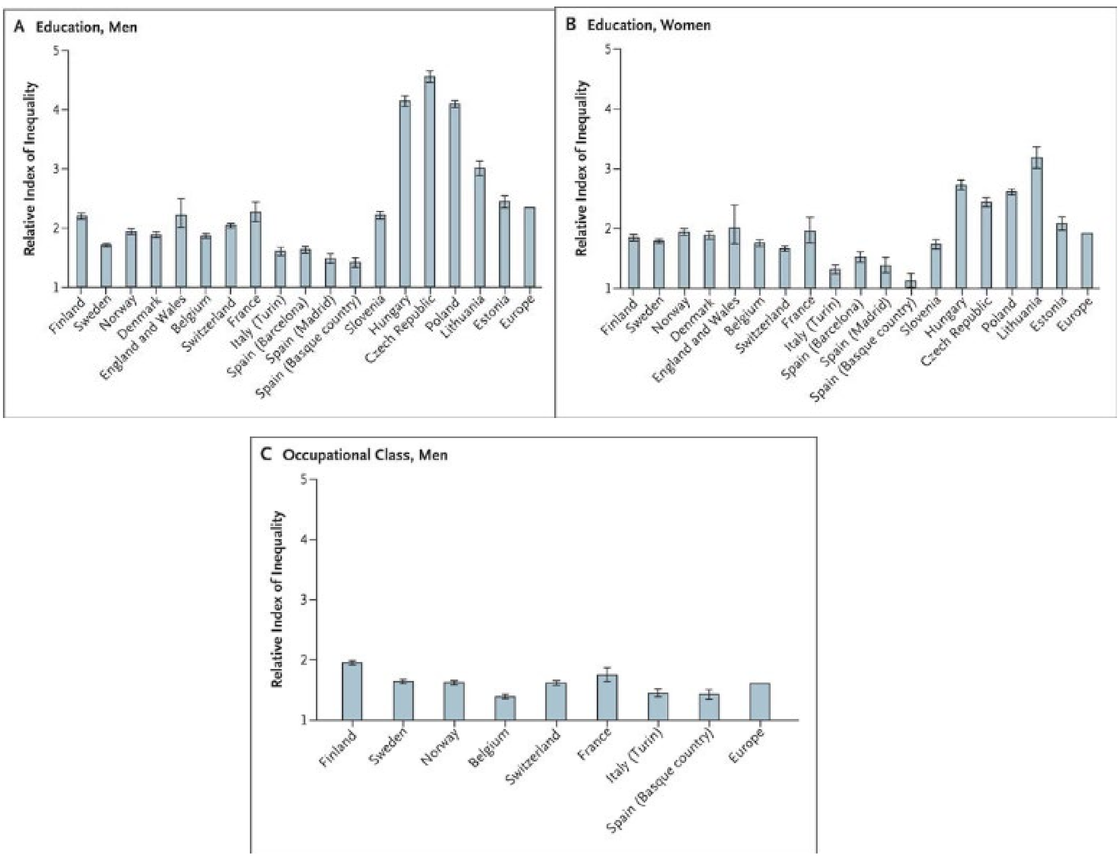


Figure 1.5: Relative inequalities in the rate of death from any cause.

Panel A shows men with lowest versus highest levels of education. Panel B shows same comparison for women. Panel C shows the mortality inequality for men in the lowest versus highest occupational class. After (Mackenbach et al., 2008).

(Townsend, 1991) elegantly outlined the relationship between social and material inequity and stress. This was acknowledged as one of the biological intermediaries driving adverse health effects of low socio-economic status by (Kaufman and Cooper, 1999). However they cautioned against simplistic hypotheses in this domain and pointed out that epidemiology as an aetiological science has been ineffective in moving towards causal explanations for many observed social parameters. Two large prospective studies attempted to disentangle the relative effects of health behaviours and socio-economic status on mortality. The Whitehall study was a prospective cohort study following nearly 10,000 participants for a mean of 19.5 years, and the French GAZEL study had 18,000 participants who were followed for just under 20 years (Stringhini et al., 2011). The health behaviours monitored were smoking, alcohol consumption, diet and physical activity. Occupation was the main parameter utilised to assess Socio-economic status, but income and education were also recorded. Socio-economic differences in mortality were similar in the two cohorts when comparing lowest versus highest occupational positions. In Whitehall, the hazard ratio was 1.62 (95% CI 1.28-2.05), and in GAZEL, 1.94 (95% CI 1.5802.39). Health behaviours attenuated the association of socio-economic status with mortality by 75% in the Whitehall, study but only by 19% in GAZEL. This difference may be explained by the differential effect of socio-economic status on health behaviours between the two studies. In Whitehall, the socio-economic gradient for smoking was 3.68 (95% CI 3.11- 4.68), whilst in GAZEL, it was only 1.33 (95% CI 1.18- 1.49). For an unhealthy diet, it was 7.42 (95% CI 5.19- 10.6) in Whitehall versus 1.31 (95% CI 1.15 -1.49) in GAZEL. The logical interpretation of this is that health behaviours are likely to be major contributors to socio-economic differences in health only where there is a marked social characterisation of health behaviours. (Petrovic et al., 2018) attempted to quantify the contribution of health behaviours to the socio-economic gradient. They conducted a systematic review of the published literature, and they concluded that a lower socio-economic position was associated with an increased risk of all-cause mortality and cardio-metabolic disorders. The gradient was explained by health behaviours to varying degrees, ranging from -43% to +261%. Further, health behaviours explained a larger proportion of the socio-economic position health gradient in studies conducted in North America and Northern Europe. Smoking was the health behaviour that contributed most to social inequalities in health.

It is also worth noting that individuals may traverse socio-economic groups across their lifecycles. (McMaughan et al., 2020) postulate that healthy ageing is primarily a function of socio-economic status, where this consists of a series of recursive statuses around the reflexive position of a person's financial situation, educational attainment, and employment status - see figure 6. They argue that a person's ability to access healthcare is mediated by socio-economic status. The idea of "access" is itself described in terms of the availability of relevant and effective services and providers, physical accessibility and affordability, the acceptability of the services and the service providers are to the patient, and how accommodating the services are to the persons requirements (McLaughlin and Wyszewianski, 2002). These five "A's" of access form a chain that is no stronger than its weakest link. Within this context, an acute hospital admission can be regarded as completely necessary – for example, in the context of an injury sustained in a road traffic accident, or it might represent the consequence of accumulated deficits in the quantum of care sought, offered and received that is mediated by variability in access related to socio-economic status.

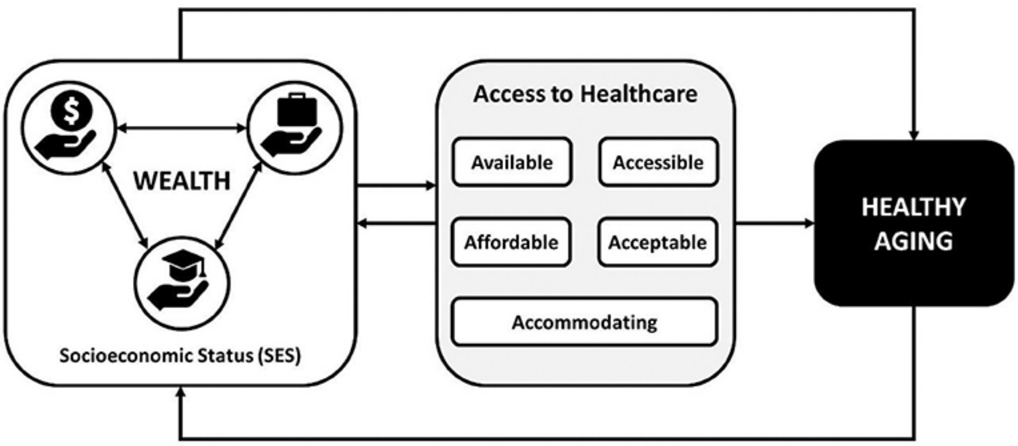


Figure 1.6: Framework by which Socio-economic status impacts on healthcare access and healthy ageing.

(after (McMaughan et al., 2020)).

1.2.3. <u>Deprivation Indices</u>

Deprivation indices are composite indices that combine several measures of socio-economic status or material deprivation. One of the first examples of using this approach in healthcare was when (Jarman, 1984) developed the underprivileged area score to identify those areas that were likely to have an increased primary care workload. Whilst Deprivation Indices operate at an area level rather than an individual level, it has been shown that once the index is calculated for a reasonably small area, the deprivation score for that area is predictive for individuals living in that area (Adams et al., 2005). Deprivation scores must be used thoughtfully at the interface of health outcomes and health service planning. (Jarman, 1984) developed a score to specifically address the issue of workload for general practitioners. Indeed, there is considerable benefit to using socio-economic parameters rather than an outcome, such as mortality, to identify high-risk populations. As pointed out by (Teljeur et al., 2019), a deceased person is not necessarily a good predictor of future healthcare needs.

The Central Statistics Office of Ireland provides deprivation index data at the Electoral Division and Small Area Population level. The Small Areas are subsets of the Electoral Divisions and relate to smaller neighbourhoods- particularly in urban areas. It is worth noting that a pragmatic approach was adopted in those locations with a small population such that no further subdivision of the Electoral Division into a Small Area was undertaken (CSO, 2022).

1.2.3.1. <u>SAHRU Index</u>

The SAHRU index (Kelly and Teljeur, 2013) utilizes unemployment, low social class, local authority rented housing and 'no-car' as indicators. Unemployment reflects a lack of access to earned income and the facilities of employment. It may also impose other pressures, such as loss of self-esteem. The unemployment indicator is defined as the proportion of the economically active populations (15 years or older) unemployed or seeking a first-time job.

Low social class is characterised by the Irish Social Class scale. This is an ordinal scale extending from score 1 (higher professional) to score 6 (unskilled manual). The conceptual basis of the scale relates to groups whose members possess the capacity to earn income through their occupations rather than connoting any status or prestige relating to those occupations. Those in classes 5 & 6 earn at the lower end of the income scale, and this can limit access to material resources and the ability to make choices in life. The proportion of the population in social classes 5 & 6 defines the 'low social-class' indicator.

Local Authority rented housing (LA), indicating non-owner occupation, is a surrogate for income in the longer term. The indicator is defined as 'the proportion of persons living in permanent private households rented from a local authority'.

Car ownership is surrogate for current disposable income. There are several facets that map to this assertion. Aside from the direct purchase cost, there are also expenses relating to insuring, taxing, maintaining, and fuelling the vehicle. Owning a car also confers advantages in terms of accessing other services. The extent to which owning a car can be viewed as discretionary operates differently across the urban/ rural divide and must be borne in mind for certain types of analysis (Teljeur et al., 2019). The 'no-car' indicator is the proportion of permanent private households with no car.

The computation of deprivation scores needs to attend to the phenomenon of 'Shrinkage' (Allik et al., 2020). The purpose of shrinkage is to move indicator values based on very small numbers closer to the mean for that indicator. This accounts for the fact that deprivation indices are calculated at a small area level where the denominator population may be quite small. Hence, a small shift in the numerator may translate into a large proportional change. The degree of shrinkage relates to the standard error associated with the small area, and, in turn, the standard error relates to the size of the population. A large population equates to a small standard error and vice versa.

The decile ranking of deprivation and the component scores of the indicators calculated from the 2016 census are summarised in Table 1.1.

Deprivation decile	Population		Indicator values (mean proportion)			
	Total	(%)	UE	SC	LA	NC
1 – least deprived	539,460	(11.3%)	0.040	0.099	0.009	0.051
2	335,496	(7.0%)	0.050	0.136	0.013	0.052
3	322,817	(6.8%)	0.055	0.151	0.016	0.059
4	388,332	(8.2%)	0.060	0.162	0.020	0.066
5	300,854	(6.3%)	0.066	0.169	0.025	0.074
6	367,818	(7.7%)	0.070	0.184	0.035	0.080
7	426,081	(8.9%)	0.076	0.194	0.049	0.096
8	461,471	(9.7%)	0.083	0.209	0.073	0.114
9	712,192	(15.0%)	0.098	0.226	0.112	0.161
10 – most deprived	907,344	(19.1%)	0.134	0.275	0.212	0.344

Abbreviations: UE, unemployment; SC, low social class; LA, Local Authority housing; NC, no car.

Table 1.1: Distribution of population and mean indicator values by deprivation decile.

****After (Teljeur et al., 2019).***

Principal Components Analysis (PCA) is a dimension reduction technique that is used to combine deprivation indicators into a single or small number of indices. To do this, a weight is developed for each variable to reflect how it correlates with other variables. Indicators associated with higher correlations receive higher weights than those associated with lower correlations. The Deprivation Index is computed by PCA with an assessment of how many components are required based on the percentage variance explained by each component. The calculated score is a continuous variable with a mean of zero. Negative scores imply less deprivation than the national average, whereas positive scores indicate more deprivation than the national average. Figure 1.7 shows the distribution of Deprivation Scores from the 2016 census.

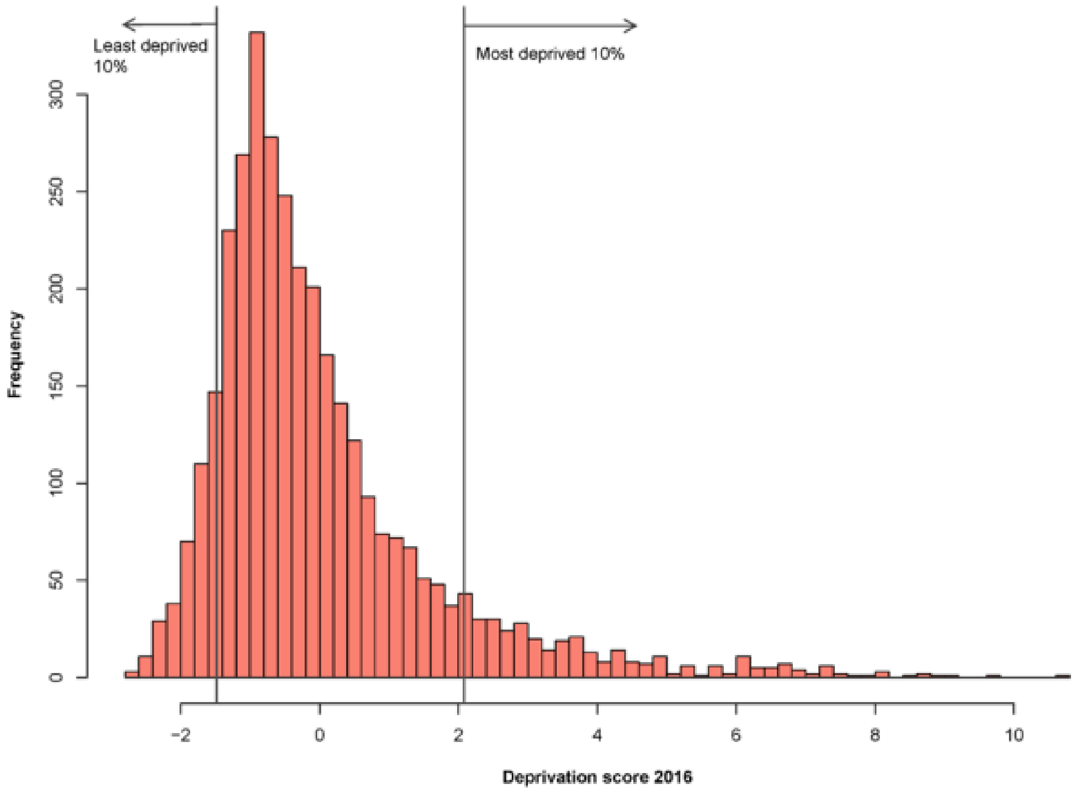


Figure 1.7: Distribution of deprivation scores (2016)

****after (Teljeur et al., 2019)***

Most of the Electoral Divisions remain stable with respect to Deprivation status over time. Comparing the 2011 and 2016 censuses, it is the case that 47% of EDs remained in the same decile, whereas 36% were within one decile of their previous ranking, and 17% had shifted by 2-deciles (Teljeur et al., 2019).

The Deprivation index demonstrates significant heterogeneity across geographic areas. High deprivation is concentrated in city centre areas (see Figure 1.8 and Table 1.2).

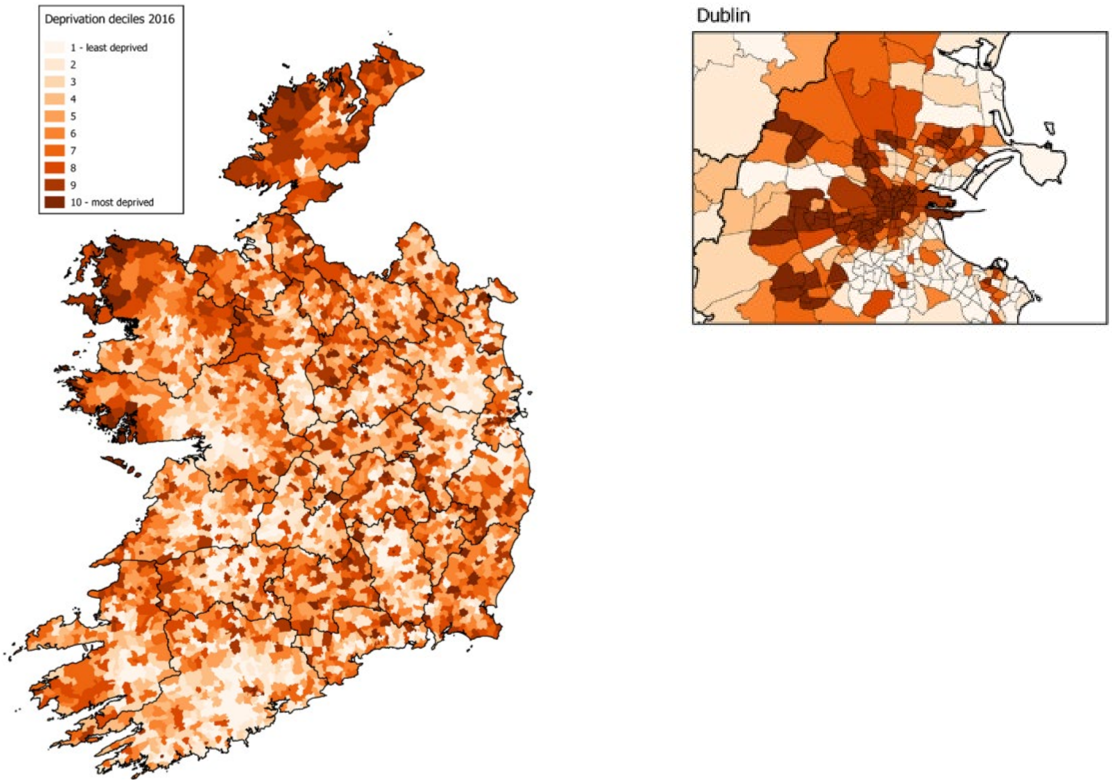


Figure 1.8: Deprivation Index Heatmap Ireland and Dublin.

**** after (Teljeur et al., 2019)***

The general temporal trend shown in the CSO data would indicate that deprivation increased between 2006 and 2011, only to reduce again by 2016. However, this means effect hides considerable electoral division variation. A shift in deprivation score by less than one standard deviation from the mean is considered as 'no-change'. Shifts of one to two and greater than two standard deviations are considered moderate and substantial, respectively. When assessing the impact of socio-economic status on outcomes over extended periods of time, it is necessary to have a mechanism for following this metric accurately over time.

County council	Population	Deprivation score		Proportion deciles 9 & 10	
		Mean	Rank	Mean	Rank
Limerick City	51,458	3.204	34	0.712	34
Waterford City	48,216	2.482	33	0.689	33
Cork City	125,657	2.105	32	0.643	32
Longford	40,873	1.840	31	0.465	22
Dublin City	554,554	1.747	30	0.546	27
South Tipperary	88,271	1.200	29	0.510	24
Louth	128,884	1.179	28	0.566	30
Carlow	56,932	1.158	27	0.553	29
Galway City	78,668	1.097	26	0.604	31
Donegal	159,192	1.067	25	0.552	28
Wexford	149,722	0.979	24	0.476	23
Offaly	77,961	0.917	23	0.522	25
Laois	84,697	0.788	22	0.525	26
Cavan	76,176	0.731	21	0.306	14
Westmeath	88,770	0.724	20	0.418	20
Monaghan	61,386	0.611	19	0.427	21
South Dublin	278,767	0.609	18	0.316	15
Sligo	65,535	0.603	17	0.383	19
North Tipperary	71,282	0.426	16	0.380	18
Mayo	130,507	0.395	15	0.324	16
Kerry	147,707	0.321	14	0.255	11
Leitrim	32,044	0.293	13	0.361	17
Kilkenny	99,232	0.269	12	0.283	13
Wicklow	142,425	0.213	11	0.272	12
Waterford	67,960	0.201	10	0.179	6
Roscommon	64,544	0.128	9	0.216	8
Clare	118,817	0.061	8	0.253	10
Galway	179,390	-0.143	7	0.237	9
Limerick	143,441	-0.201	6	0.168	4
Kildare	222,504	-0.206	5	0.206	7
Meath	195,044	-0.343	4	0.077	2
Fingal	296,020	-0.359	3	0.159	3
Cork	417,211	-0.409	2	0.177	5
Dún Laoghaire-Rathdown	218,018	-1.244	1	0.073	1

Table 1.2: County Councils ranked by population-weighted 2016 deprivation scores with corresponding proportions in deciles 9&10.

****After (Teljeur et al., 2019).***

1.2.3.2. <u>The 2016 POBAL HP Deprivation Index for Small Areas (SA)</u>

There are many similarities between the approach adopted to calculate the POBAL HP score and the SAHRU score. Of course- they derive from the same census data. The POBAL HP score has become widely adopted across government departments- a particular feature in its design is the fact that it accurately captures rural as well as urban deprivation (Haase and Pratschke, 2012). It aspires to act as an index of relative affluence and deprivation, as well as representing a sophisticated measure of well-being at a 'society' level that can be tracked over time. It derives from a working definition of deprivation by (Coombes et al., 1995).

> ***"The fundamental implication of the term deprivation is of an absence – of essential or desirable attributes, possessions and opportunities which are considered no more than the minimum by that society."***

The measurement model of the POBAL HP deprivation index is shown in figure 1.9. The POBAL HP deprivation index is calculated using a multiple group means and covariance structure method- this means it is possible to measure the change occurring in the mean of latent variables between censuses (Haase and Pratschke, 2012).

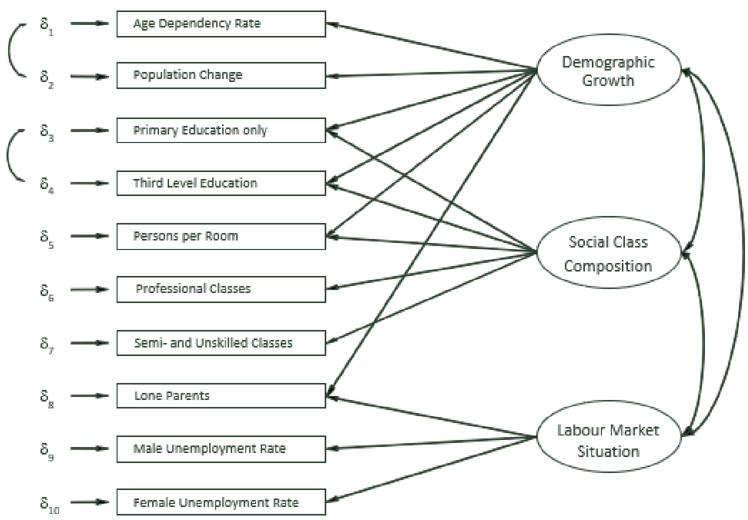


Figure 1.9: POBAL HP Deprivation Index Measurement Model.

The POBAL HP deprivation index is derived by a factor analytical approach. This is similar to the SAHRU approach. Three dimensions of affluence/ disadvantage have been identified that map to Demographic profile, social class composition and labour market situation.

In this index, demographic profile is conceptualised as primarily a marker of rural affluence/ deprivation. The theory underlying this assumption is that long-term unemployment in rural areas manifests as agricultural under-employment and emigration, whereas in urban areas, one finds unemployment blackspots. Emigration from deprived rural areas represents a mismatch between the level of skills, and education attained set against the opportunities that are available. Emigration is socially selective and tends to be dominant in working-age groups with post-secondary-level education. Those left behind are economically dependent and have low levels of educational achievement. The demographic profile is measured by six indicators:

- Percentage change in population over last 5 years (positive association)
- Percentage population under 15 years/ over 64 years of age (negative association)
- Percentage of the population with primary school education ONLY (negative association)
- Percentage of the population with a third-level education (positive association)
- Percentage of the households with children aged under 15 years headed by a single parent (positive association)
- The mean number of people per room (positive association)

Social class composition is equally relevant to urban and rural dwellers. Social class background impacts areas such as educational achievement, health, housing, crime, and economic status. It tends to be stable over time and, crucially, constitutes a key factor in the inter-generational transmission of economic, cultural and social assets. Those areas with a weak social class profile tend to have higher unemployment rates, are more likely to experience poor pay and working conditions and have poor housing conditions.

Social class composition is measured by five indicators:

- The percentage of the population with primary school education only (negative association)
- The percentage of the population with a third-level education (positive association)
- The percentage of households headed by professionals or managerial and technical employees, including farmers with 100 acres or more (positive association)
- The percentage of households headed by semi-skilled or unskilled manual workers, including farmers with less than 30 acres (negative association)
- The mean number of people per room (negative association)

The labour market situation primarily affects urban areas. Unemployment, and particularly long-term unemployment, are the principal cause of disadvantage at a national level and are responsible for the concentrated forms of multiple disadvantages found in urban areas. There are three indicators measured to reflect Labour Market Situation:

- Percentage of households with children aged under 15 years that are headed by a single parent (negative association)
- Male unemployment rate (negative association)
- Female unemployment (negative association)

Each of these dimensions is calculated in the same way for each census wave and then combined to form an Absolute Index Score and a Relative Index Score. The absolute index score can be followed between censuses, whereas the relative index score is specific to a given census wave. In essence, the Absolute Index Score reflects changes in the overall economic position between census waves, whereas the Relative Index Score relates to differences between areas at the time of the census in question. Table 1.3 summarises the distribution of the Absolute and Relative POBAL HP Deprivation Scores between 2006 and 2016.

HP Index	Number of SAs	Minimum	Maximum	Mean	Std. Deviation
2006 **Absolute** Index score	18,488	-41.5	38.3	0.0	10.0
2011 **Absolute** Index score	18,488	-35.6	30.5	-6.6	9.5
2016 **Absolute** Index score	18,488	-40.9	35.5	-4.2	9.9
2006 **Relative** Index score	18,488	-41.5	38.3	0.0	10.0
2011 **Relative** Index score	18,488	-30.8	40.0	0.0	10.0
2016 **Relative** Index score	18,488	-39.3	40.3	0.0	10.0

Table 1.3: POBAL HP Deprivation Scores 2006-2016.

A key strength of the POBAL HP Deprivation index is its ability to reflect Absolute HP Deprivation scores over time (see figure 1.10). This is a unique feature amongst commonly used indices and is related to the fact that the POBAL HP Deprivation Index uses Confirmatory Factor Analysis in its construction. This means that it is not necessary to default to decile rankings for between-census comparisons, and the creators argue that it is more sensitive to the level of deprivation experienced within a population group (Haase and Pratschke, 2012).

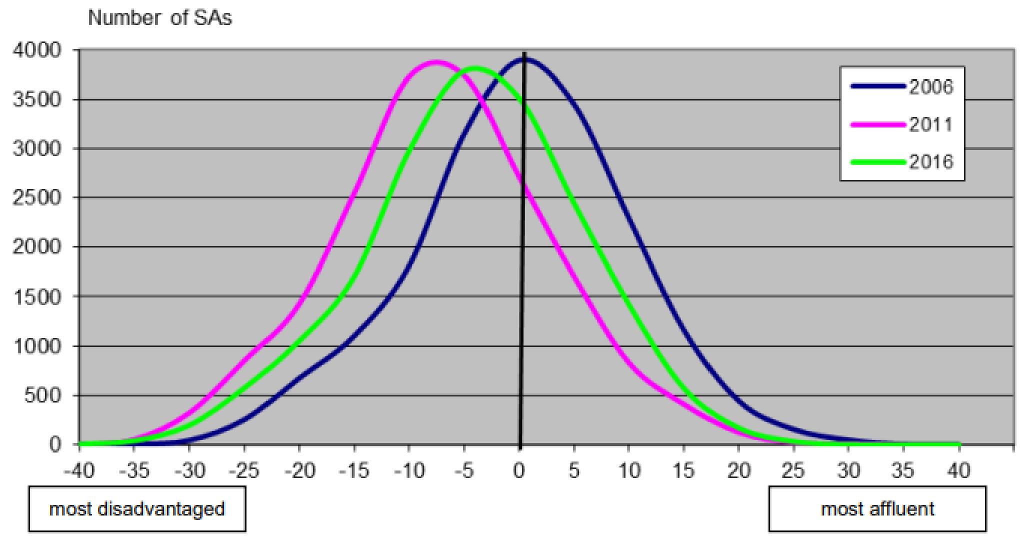


Figure 1.10: Distribution of POBAL HP Absolute Index Score 2006-2016.

Chapter 2 . The Relationships between Socio-economic status and multi-morbidity

2.1. Abstract

Background: Areas of low socio-economic status (SES) have a disproportionate number of emergency medical admissions; we quantitate the profile of multi-morbidity related to SES.

Methods: We developed a logistic multiple variable regression model based on over 15 years of hospital data to examine the effect of sociodemographic and morbidity status on hospital outcomes.

Results: Admissions from the low SES cohort were a decade younger and had a shorter hospital stay, and lower 30-day episode mortality outcomes. The number of morbidities was equivalent between groups, but the more disadvantaged were more likely to have a respiratory diagnosis or diabetes.

Conclusion: Low SES emergency medical admissions present more than a decade earlier than high SES persons but have equivalent multi-morbidity.

2.2. Introduction

Morbidity, broadly speaking, may be considered to be present when an individual possesses symptoms that indicate ill health or the presence of disease. Morbidity may also represent the complications or undesirable outcomes of therapy or the rate of illness in a select population group (Merriam-Webster, 2002). It is generally accepted that the 'poor', as in persons from more deprived backgrounds, tend to consume more hospital resources (Cookson and Laudicella, 2011). This may be because low socio-economic status (SES) is associated with multi-morbidity; the onset of multi-morbidity was found to occur 10–15 years earlier in people living in the most deprived compared with the most affluent areas (Barnett et al., 2012).

Our hospital catchment area contains many small areas characterised by a high deprivation status (Walsh et al., 2004). However, as practicing clinicians, we have no clear view as to whether individuals with different SES backgrounds have a different morbidity profile at the time of an emergency medical presentation.

Instruments to assess morbidity typically employ administrative data such as hospital discharge codes to construct a risk profile; the assessment can be simple code evaluation (a single hospitalisation with limited codes) or more complex (inpatient and outpatient encounters and many codes screened) (Tonelli et al., 2016). Previous work, such as that of (Barnett et al., 2012), identified 40 morbidities and were informed by a systematic review of multi-morbidity measures (Diederichs et al., 2011) - the Quality and Outcomes Framework of the UK General Practice contract and health service planning by NHS Scotland. Apart from data sources that might be specific to the United Kingdom, a Canadian group proposed an alternative approach using validated algorithms that used ICD9 CM/ICD-10 to ascertain the presence or absence of 40 morbidities (Tonelli et al., 2016). From these, they identified a panel of 30 chronic conditions that could potentially facilitate the study and surveillance of multi-morbidity. It is reasonable to assume that, at a steady state, a given rate of population comorbidity will translate into a proportionate rate of emergency hospitalisation; comparison between the documented comorbidities from different SES populations might then reasonably permit inference regarding the prevalence or comorbidity within these different SES small areas.

This study, therefore, investigates whether our catchment area population, heavily weighted to low SES status, possesses a disproportionate level of multi-morbidity and whether this can be determined from the data captured routinely using the hospital administrative systems. We have examined the last 16 years of acute medical admissions (2002-2017) comprising 106,586 episodes of care at St James' Hospital, Dublin, in order to investigate the relationship between the multi-morbidity in emergency medical admissions related to low or high socio-economic status.

2.3. Methods

2.3.1. <u>Background</u>

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 Emergency Department to an Acute Medical Admission Unit, the operation and outcome of which have been described elsewhere (Rooney et al., 2008, Conway et al., 2014). As a city centre hospital, St James's admits people resident elsewhere but working in the capital in addition to visitors to Dublin who became acutely ill. The number of emergency medical admissions residents in the catchment area was 74.5%; this compares with a figure of 59% for Emergency Department presentations where the social influences on emergency department visitations on two London hospitals have been examined (Beeknoo and Jones, 2016b).

2.3.2. <u>Data collection</u>

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 electronic patient record, the emergency room and laboratory systems. HIPE is a national database of coded discharge summaries from acute public hospitals in Ireland (O'Loughlin et al., 2005, O'Callaghan et al., 2012). 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.

2.3.3. Multi-morbidity Instrument

Hospital HIPE codes (O'Loughlin et al., 2005) were interrogated to construct a measure of multi-morbidity. To devise the score, we searched ICD-9 hospital episode discharge codes (back-mapping ICD-10 codes to ICD-9 as appropriate) based on the definition proposed by the US Department of Health and Human Services for chronic physical or mental health disorders, that limit people 'in activities that they generally would be expected to be able to perform'. These ICD codes were similar to those proposed by the Canadian group for multi-morbidity (Tonelli et al., 2015) and the work of (Quan et al., 2008); they were combined by system into the following ten groups: (i) cardiovascular, (ii) respiratory, (iii) neurological, (iv) gastrointestinal, (v) diabetes, (vi) renal, (vii) neoplastic disease, (viii) others (including rheumatological disabilities), (ix) ventilatory assistance required and (x) transfusion requirement. We have previously detailed the ICD-9 codes utilised based on the definition proposed by the US Department of Health and Human Services in their supplementary Table (Ozminkowski et al., 2000). In addition, we searched other hospital databases for evidence of diabetes (Diamond database), respiratory insufficiency (FEV1 < 2 L data pulmonary function laboratory), troponin status (high sensitivity troponin > 25 ng/L) (Courtney et al., 2014), low albumin (<35 G/dL) and anaemia (haemoglobin levels < 10 G/dL) or chronic renal insufficiency - MDRD < 60 mL/min*1.73 m^2 (Stevens and Levin, 2013). The 'morbidity score' for each individual's clinical episode during the study was weighted by its relative importance against the 30-day mortality outcome in the multiple variable regression analysis. This study had no interventional component, used anonymised routinely collected data, complied with data protection legislation and was undertaken with the approval of hospital authorities, hence did not require approval from our institutional ethics committee.

2.3.4. Deprivation Instrument

The Republic of Ireland census (Central Statistical Office) reports 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). Deprivation metrics have been determined by the Small Areas Health Research Unit (SAHRU) of Trinity College Dublin using a methodology similar to (Townsend, 1987) and (Carstairs and Morris, 1989) to derive a Deprivation Score using principle components analysis (PCA); a weighted combination of four indicators, relating to unemployment, social class, type of housing tenure and car ownership (Kelly and Teljeur, 2013). We have previously demonstrated the utility of the SAHRU classification of Deprivation in terms of predicting acute 30-day acute hospital mortality (Conway et al., 2013), admission and readmission rate incidences (Cournane et al., 2015a) and hospital costs following an emergency medical admission (McCabe et al., 2017). The assignment of patients to small area population areas used the ArcGS Geographic Information System software implementation of the well-known Point-in-Polygon algorithm as outlined by Shimrat (Shimrat, 1962).

2.3.5. **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. For count data (hospital LOS and readmissions), 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, 2010). 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 (IRR).

We adjusted the prediction of outcome (30-day in-hospital mortality) for known predictor variables that included multi-morbidity score, the Deprivation Index, age group (5-year groups), single parent status and higher educational attainment status (higher education > 18 years). We employed a logistic model with a robust estimate to allow for clustering; the correlation matrix thereby reflected the average discrete risk attributable to each of these predictor variables (Silke et al., 2010). Logistic regression analysis identified potential mortality predictors and then tested those that proved to be significant univariate predictors ($p<0.1$ by Wald test) to ensure that the model included all variables with predictive power. We used the margins command in Stata 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 multiple variable model (logistic or 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.

Adjusted odds ratios (OR) and 95% confidence intervals (CI) were calculated for those predictors that significantly entered the model ($p<0.10$). Statistical significance at $P<0.05$ was assumed throughout. Stata v.15 (Stata Corporation, College Station, Texas) statistical software was used for analysis.

2.4. Results

2.4.1. Patient Demographics

During the 16-year study period (2002-2017), there were a total of 106,586 episodes of medical emergencies in 54,928 unique patients admitted through the Emergency Department. These episodes represented all emergency medical admissions, including patients admitted directly into the Intensive Care Unit or High Dependency Unit.

The demographic characteristics (Table 2.1) are outlined with a division of 'low' or 'high' socio-economic status (lower/higher cut at Deprivation Quintile 3 – i.e. Q4/5 low SES) at presentation and tabulated (to allow group comparisons) by our Co-morbidity Score, Charlson Index (Charlson et al., 1987) and Sepsis status (Chotirmall et al., 2014b). Admissions with a lower SES were younger, 66.3 years (IQR: 47.1, 79.5) vs. 77.5 years (61.8, 84.8) and had a shorter hospital stay of 6.1-day (2.7, 13.6) vs. 6.8-day (2.9, 16.3), and a lower 30-day episode mortality outcome (5.6% vs. 7.1%). These younger admissions from the low SES catchment area were less likely to have higher Co-Morbidity Scores (≥ 8 points – 40.8% vs. 45.4%), Charlson Index (Grade 2 - 26.5% vs. 24.8%) but had similar sepsis scores. From an overall clinical perspective, one, could regard the groups as essentially equivalent in risk profile, albeit with an age difference of approximately one decade.

2.4.2. Comparison of Disease Profiles (Table 2.2)

In order to screen for morbidity, we used the classification system proposed by the US Department of Health and Human Services for chronic physical or mental health disorders, and further screened ICD-10 HIPE hospital discharge codes. We were slightly restricted in data analysis for two reasons. Firstly, Ireland used ICD-10-CM discharge coding from 2005 and our search algorithms could only interrogate this source rather than the International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) used up to this point. Second, we can only compute accurate population admission incidence rates for those residing within the hospital catchment area; as a city centre hospital (with a large transient population of worker's resident outside the area and visitors), only approximately 74.5% of emergency admissions resided within the catchment area. This compares with a figure of 59% for ED presentations where the social influences on emergency department visitations in two London hospitals have been examined (Beeknoo and Jones, 2016b).

Notwithstanding these limitations, the disease profile showed distinct differences related to the SES of these emergency admissions. Emergency admissions with primary diagnoses of respiratory (32.8% vs. 22.1%) or mental disorders (16.0% vs. 9.9%) occurred with a high frequency in admissions from a lower SES background. Cardiovascular disease was somewhat higher in those from lower SES areas (9.6% vs. 8.2%). Diabetes was much more evident in the lower SES areas (11.8% vs. 8.8%). The overall rate of admission for alcohol-related or with a detoxification classification was not that high, but again very different between low and high SES areas (4.3% vs. 1.6%). Gastro-intestinal disorders were more evident within the low SES admitted cohort (26.7% vs. 23.3%). In contrast, disorders related to cognition or behaviour related were more frequent in the older population (10.4% vs. 7.6%) admitted from the higher SES small areas.

2.4.3. Multi-morbidity construct and Socio-Economic Status (Table 2.3)

Overall, the number of morbidities (median 3; (IQR 2,4) and the attributed weighted score (median 6.0; (IQR 3.8, 8.6) was similar between low and high SES admission cohorts. The number of morbid conditions by SES area of residence was marginal ($F = 5.8$, $=0.02$) contrasting with the much higher weighted score of morbidity ($F = 24.5$, $P<0.001$) suggesting that low SES areas of residence may not necessarily have more multi-morbidity by count but that it was overrepresented with higher risk categories. Of course, age has an important influence. The decade age difference between the admitted cohorts from the low and high SES areas has to be remembered. The percentage of each admission cohort with morbidity scores in the range of <6, 6-10, 10-13, 13-16 and >16 points (Fig 2.1) was 45.7%, 40.1%, 10.9%, 2.4% and 0.8% low SES group, and for 48.3%, 38.7%, 10.1%, 2.0% and 0.8% high SES group respectively.

We regressed the significant mortality predictors against SES to test the dependency of these predictors and the small area of residence. Persons living in areas with low SES were more likely to have a respiratory disease – OR 1.39 (95% CI: 1.29, 1.49) and to require ventilation – 1.27 (95% CI: 1.03, 1.56) and to be admitted with Diabetes – 1.54 (95% CI: 1.37, 1.75) or Gastro-intestinal disease - 1.35 (95% CI: 1.24, 1.49). They were less likely to have a Neurological – 0.66 (95% CI: 0.61, 0.71), Cardiovascular – 0.79 (95% CI: 0.73, 0.85) or renal - 0.59 (95% CI: 0.55, 0.64) admission or to require a blood transfusion – 0.81 (95% CI: 0.65, 1.00). There was no difference in presentations related to sepsis, neoplasm or other assorted disorders.

2.5. Discussion

These data demonstrate that persons ordinarily resident in disadvantaged small areas are admitted with an emergency medical condition more than a decade earlier than people resident in more affluent localities. However, broadly speaking, admissions, irrespective of socio-economic status, appeared to have comparable multi-morbidity at the time of admission - as determined either from the absolute number of disease systems or the weighted score of morbidity based on outcomes. That is to say, we found that the overall number of morbidities (median 3; (IQR 2,4) and the attributed weighted score (median 6.0; (IQR 3.8, 8.6) were similar between low and high SES admission cohorts. However, that does not imply that there were no significant differences in disease profiles and resultant consequences between the low and high SES cohorts. Low SES presentations had more respiratory (OR 1.39), diabetes (OR 1.54) and gastro-intestinal disease (1.35) but fewer neurological (0.66), cardiovascular (0.79) and renal (0.59) admissions and less transfusion requirement – 0.81 (95% CI: 0.65, 1.00); low SES also required more ventilatory intervention (OR 1.27),

These multi-morbidities strongly correlated with all outcomes, including 30-day hospital mortality, hospital LOS and future readmissions; the odds ratios for 30-day hospital mortality were more than twofold for 6 of 11 predictive parameters, more than threefold for two and more than fivefold for one. Overall, the people from the higher SES cohort were at higher risk and had worse 30-day mortality outcomes at any given morbidity score level (Fig 2.1). Individuals manifesting multi-morbidities typically have a lower quality of life, and a higher degree of disability, psychological distress, risk of mortality, and utilisation of health (and social) services - than if one considers their chronic conditions in isolation or for individuals with a single chronic condition (Boyd and Fortin, 2010). In terms of addressing the fundamental question as to how the low SES population have an emergency medical admission a full decade earlier than their better-off peers, it is a conundrum as it could be due to exposure to risk from an earlier age or a higher burden of total exposure over time. Clearly, however, it is not equal for all disease processes as there are systematic differences, between low and high SES areas, in terms of diabetes, respiratory, gastro-intestinal neurological and renal disease. This may be due to different rates of progression of disease between major physiological systems – respiratory would appear to have a particular impact on individuals from low SES areas.

These data also show that morbidity is very common in emergency medical admissions, whether from low or higher socio-economic backgrounds; 85.2% and 83.9% of admissions from low and high socio-economic backgrounds had two or more morbidities, and 36.8% and 34.6% had four or more respectively. It is not surprising, perhaps that hospital admissions should have higher estimates of morbidities than 'In-community' studies; however, the discrepancy from prior estimates is remarkable. Of course, the screening of hospital laboratory or other databases containing patient information or characteristics such as anaemia, hypoalbuminaemia, elevated urea or creatinine, troponin abnormality or elevated blood pressure will quantitate morbidity that may not have been overlooked but simply not documented in the discharge coding; for example, 33.8% of the population had not been coded (ICD9/10 HIPE discharge code) for renal insufficiency (MDRD < 60 mL/min*1.73 m^2).

Previous estimates of morbidity within populations were based on surveys such as (Tonelli et al., 2016), who found that approximately one-quarter of the surveyed population (inpatients and outpatient claims data) had multi-morbidity (2 or more conditions) and 12% of three or more conditions. The prevalence of 26% appeared similar to the results of (Barnett et al., 2012). Our figures of 84% overall are quite different for an emergency admitted medical population – perhaps this shows the limitations of administrative data based on hospital discharge codes with consistent underestimates of the presence of co-morbidity (Powell et al., 2001). The very high level of multi-morbidity we have documented in emergency medical admissions perhaps could question whether cost containment measures, centred around admission avoidance, are an appropriate core strategy for such a population - in view of the limited evidence from randomised controlled trials that such strategies are workable (Shepperd et al., 2016).

It is also generally agreed that multi-morbidity rises with age. In the Basque region, two administrative databases suggested that multi-morbidity was higher in regions of low socio-economic circumstances (Orueta et al., 2014). The data of (Barnett et al., 2012) indicate that although 23.2% of the population was multimorbid and that this increased with age, the absolute number of people with multi-morbidity was higher in those younger than 65 years. Another age- and sex-standardised estimated prevalence rate of multi-morbidity was 19.0% in the general population, but of those with multi-morbidity, 70.2% were aged less than 65 years (Agborsangaya et al., 2012). Our data, related to 3 age-based cohorts (< 50 yr., >= 50 & < 70 yr., and >=70 yr.), indicated that for the admitted population of medical emergencies, multi-morbidity was present in 67.8%, 85.2% and 93.5% of these respective cohorts. Again, the level of multi-morbidity is quite different from the data previously cited in the literature. Of course, the age discrepancy at the time of admission between low and high SES populations related to areas or residence, with respective median ages for low SES being 66.5 years (IQR: 47.1, 79.2), and high SES 76.8 years (IQR: 61.7, 84.3) results in a bimodal age distribution for the admitted population and this limits direct comparisons. But our data indicate that whatever the age discrepancy between admissions rated to SES, at the time of their admission, they have comparable levels of comorbidities.

Physical multi-morbidity has been found to be strongly associated with unplanned admission to the hospital, including admissions that were potentially preventable. This risk of admission to the hospital was exacerbated by the coexistence of mental health conditions and socio-economic deprivation (Payne et al., 2013). Of course, persons from deprived area use more hospital resources (Cournane et al., 2015a, Conway et al., 2016b) largely due to the cumulative impact of more frequent readmissions driving up overall costs (McCabe et al., 2017).

The issue being investigated in the present work was whether the difference between the disadvantaged and better-off populations could be attributed to a discrepancy in multi-morbidity between these populations rather than other social or economic issues. A Polish national study of multi-morbidity was conducted in hospitalised patients and found that co-morbidity significantly increased with age, notably due to the increasing prevalence of non-cardiovascular disease, including diabetes, chronic kidney disease, hypercholesterolemia and anaemia. In this study, 83% of patients were living with three or more co-morbidities (Agborsangaya et al., 2012). The rate of increase of multi-morbidity with age was estimated to be 8.1% in those aged 25–34 but up to 76.1% for those aged ≥75 years; mixed physical and mental (40% of all multi-morbidity) was the most common type of multi-morbidity in those aged <55 years and was two- to threefold more common in the most deprived compared with the least deprived in most age groups (McLean et al., 2014). Our data suggests, however, that most emergency medical admissions to acute hospitals do have a physical rather than mental component but that certain entities such as respiratory, gastro-intestinal, diabetic and alcohol-related illnesses are overexpressed and may be a manifestation of social or behavioural influences on lifestyle.

2.6. Conclusion

The overall conclusions are that a younger cohort (at the time of emergency medical admission) from a low socio-economic background has equivalent multi-co-morbidity status to the older higher socio-economic group cohort but that the disease profile is considerably different – possibly attributable to the age difference at the time of presentation. This may represent the phenotypic expression of adverse health outcomes related to differences in lifestyle as evidenced by the over-representation of respiratory and diabetes illness in the less affluent group.

Table 2.1: Characteristics of Emergency Medical Admission Episodes by Socio-economic Status

	High SES (N = 6773)	Low SES (N = 61928)	p-value
Age (yr.)			
Mean (SD)	71.43 (18.45)	62.59 (20.16)	<0.001
Median (Q1, Q3)	77.5(61.8, 84.8)	66.3 (47.1, 79.5)	
Length Stay (day)			
Mean (SD)	17.87 (38.56)	15.29 (34.98)	<0.001
Median (Q1, Q3)	6.8 (2.9, 16.3)	6.1 (2.7, 13.6)	
Gender			
Male	3032 (44.8%)	28708 (49.0%)	<0.001
Female	3741 (55.2%)	29917 (51.0%)	
30-day Hospital Mortality			
Alive	6294 (92.9%)	55344 (94.4%)	<0.001
Dead	479 (7.1%)	3281 (5.6%)	
Morbidity Score			
< 6	1391 (28.1%)	13216 (31.9%)	<0.001
>=6 < 8	1317 (26.6%)	11256 (27.2%)	
>=8 < 12	1762 (35.6%)	13303 (32.1%)	
>=12 < 20	483 (9.8%)	3617 (8.7%)	
Charlson Index			
0	3148 (46.6%)	24687 (42.2%)	<0.001
1	1931 (28.6%)	18319 (31.3%)	
2	1678 (24.8%)	15474 (26.5%)	
Sepsis Group			
1	5089 (75.1%)	43928 (74.9%)	0.924
2	1395 (20.6%)	12195 (20.8%)	
3	289 (4.3%)	2502 (4.3%)	

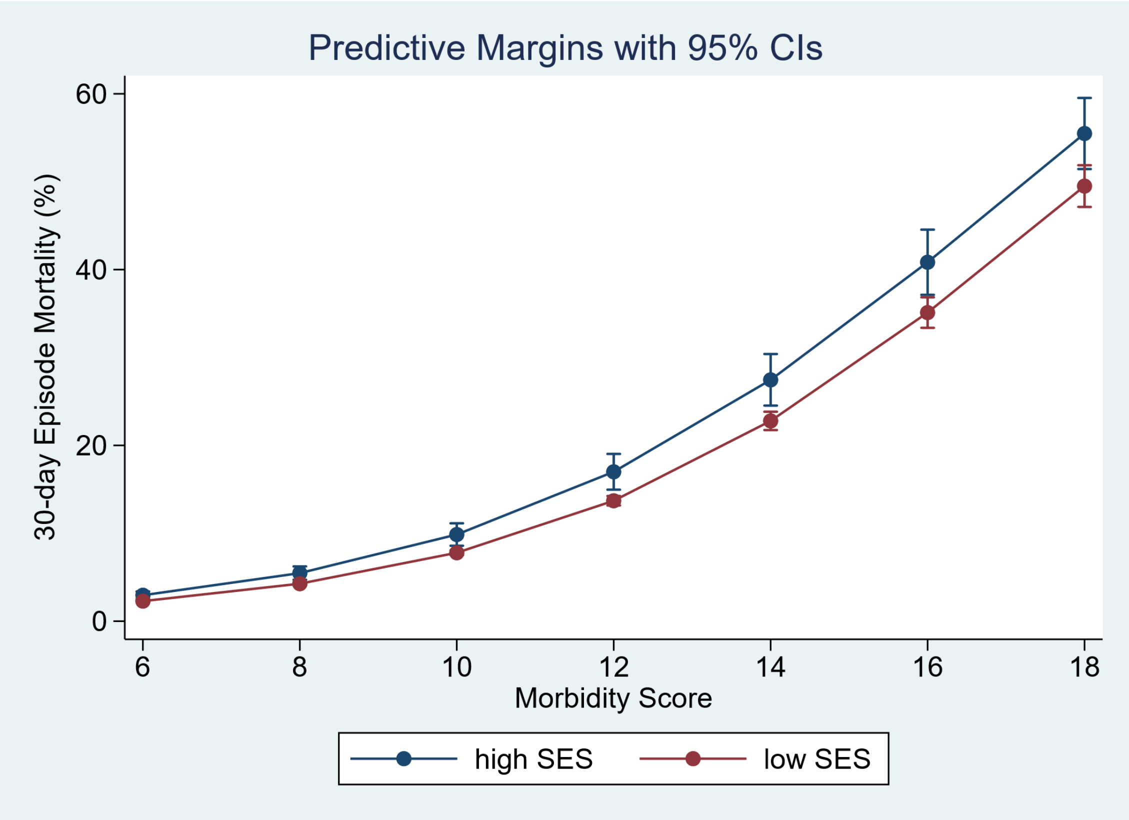
Table 2.2: Disease Profile of Emergency Medical Admission Episodes by Socio-economic Status.

	High SES (N = 6773)	Low SES (N = 61928)	p-value
Cardiovascular			
0	6216 (91.8%)	53020 (90.4%)	<0.001
1	557 (8.2%)	5605 (9.6%)	
Respiratory			
0	5279 (77.9%)	41598 (67.2%)	<0.001
1	1494 (22.1%)	20330 (32.8%)	
Mental Disorder			
0	6103 (90.1%)	49260 (84.0%)	<0.001
1	670 (9.9%)	9365 (16.0%)	
Alcohol Related			
0	6665 (98.4%)	56098 (95.7%)	<0.001
1	108 (1.6%)	2527 (4.3%)	
Skin Disorder			
0	6545 (96.6%)	56130 (95.7%)	0.001
1	228 (3.4%)	2495 (4.3%)	
Gastro-Intestinal			
0	5192 (76.7%)	45392 (73.3%)	<0.001
1	1581 (23.3%)	16536 (26.7%)	
Diabetes			
0	6160 (91.2%)	51604 (88.2%)	<0.001
1	597 (8.8%)	6876 (11.8%)	
Cognition/Behaviour			
0	6071 (89.6%)	54154 (92.4%)	<0.001
1	702 (10.4%)	4471 (7.6%)	

Table 2.3: Multivariable Fractional Polynomial Regression of Mortality Predictors by low SES status

Variable	Odds Ratio	Std. Err.	z	P>|z|	[95% Interval]	Conf.
Cardiovascular	0.79	0.03	-6.0	0.00	0.73	0.85
Respiratory	1.39	0.05	8.7	0.00	1.29	1.49
Neurological	0.66	0.02	-11.0	0.00	0.61	0.71
Gastro-Intestinal	5	0.06	6.4	0.00	1.24	1.49
Diabetes	1.54	0.10	6.9	0.00	1.37	1.75
Renal	0.59	0.02	-14.6	0.00	0.55	0.64
Neoplasm	0.94	0.06	-0.9	0.34	0.82	1.07
Sepsis	0.98	0.04	-0.6	0.54	0.90	1.06
Others	0.95	0.04	-1.4	0.17	0.87	1.02
Ventilation	1.27	0.14	2.2	0.03	1.03	1.56
Transfusion	0.81	0.09	-1.9	0.05	0.65	1.00
_cons	32.63	1.50	75.8	0.00	29.82	35.71

Figure 2.1: Relationship between Multi-morbidity score and 30-Day mortality*.



**** The 30-day hospital episode mortality outcome was non-linearly related to the Multi-Morbidity Score The predicted probabilities were derived from the multiple variable logistic model; the effect is plotted based on the latter prediction. The older high SES group had a higher mortality predicted at any given morbidity level, but the overall trend of mortality / morbidity relationship was similar.***

Chapter 3 . **Examining acute hospital admission and readmission rates through the lens of classical and multidimensional deprivation models.**

3.1. Abstract

Background: Classical deprivation instruments used 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 the street level. The implications for hospital catchment area statistics appear not to have been considered.

Methods: Between 2002 and 2016, we calculated the admission and readmission rate incidence for all emergency medical admissions (96,526 episodes in 50,731 patients) from the 74 small areas within the hospital catchment area. We compared a classical (SAHRU) to a multi-dimensional (POBAL HP) deprivation instrument for two Irish Censuses (2006 and 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. On Poisson Regression modelling, the SAHRU classical instrument had a higher prediction level IRR of 1.48 (95% CI: 1.47, 1.49) compared with POBAL HP of 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 emergency medical admission.

Conclusion: Deprivation influences hospital incidences rates for emergency medical admissions and readmissions; instruments focusing on 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.

3.2. Introduction

Deprivation has been defined by Townsend as a state of "observable and demonstrable disadvantage relative to the local community to which an individual belongs" (Townsend, 1987). Socio-economic deprivation has been shown to increase hospital utilisation (Zhao et al., 2011) and hence health care costs (Tian et al., 2012, Cournane et al., 2015a, Cournane et al., 2015c). Deprivation is a very significant determinant of the incidence rate of emergency medical admissions (Cournane et al., 2015c, Conway et al., 2015b). Ultimately although life expectancy has increased over time, irrespective of the level of deprivation within English regions, there has been little improvement in the overall variation in life expectancy across such regions (Newton et al., 2015). Deprivation must therefore be of great interest to practicing clinicians. It is particularly relevant to our catchment area, which is predominantly an inner city with a high intrinsic of rate of deprivation (Walsh et al., 2004). A complicating factor in assessing the impact of deprivation is the trajectory of inward and outward migration from inner city Dublin alongside the change in the socioeconomic makeup of communities (Walsh and Walsh, 2008). We have investigated the influence of deprivation on the acute 30-day acute hospital mortality (Conway et al., 2013), readmission rates (Cournane et al., 2015b) and hospital costs following an emergency medical admission (McCabe et al., 2017) with emphasis on the population of lower socio-economic status (SES).

The precise explanation as to why discrete populations acquire 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 (Kelly and Teljeur, 2007). Our traditional Irish Deprivation Index was devised by the SAHRU investigators (Trinity College, Dublin), using principal 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 (Kelly and Teljeur, 2007). The methodology is very similar to other classical Deprivation Indexes, including those by (Townsend, 1987) and (Carstairs and Morris, 1989). Deprivation status for small communities is measured by comparing the standardised differences of selected parameters (Kelly and Teljeur, 2013, Morgan and Baker, 2006) with the population norms; these parameters can then be related to healthcare (or other) outcome variables (Conway et al., 2013, Cournane et al., 2015a, McCabe et al., 2017). 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 are to employ a multi-dimensional instrument. Rather than the traditional factor analytical approach, these have been developed based on an "a-priori" conceptualization of different dimensions of affluence/disadvantage, such as Demographic Profile, Social Class Composition and Labour Market Situation. This is the POBAL Haase Pratschke Instrument (Haase and Pratschke, 2012). Here the emphasis is on capturing the fine details at the level of a smaller population area than the Electoral Division. Electoral Divisions (3409 units) have populations ranging from under 100 to over 32,000 people, 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 households. This effectively provides street-level information on the Irish population. The move away from the larger Electoral Division towards a 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 how such a change in approach would affect the hospital's interest in understanding and predicting 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 HP District Electoral Division ranks from the 2006 and 2011 Censuses.

3.3. Methods

3.3.1. Background

St James's Hospital, Dublin, serves as a secondary care centre for emergency admissions in a catchment area with a population of 210,000 adults. All emergency medical admissions are admitted from the ED to an Acute Medical Admission Unit, the operation and outcome of which have been described elsewhere (Rooney et al., 2008, Conway et al., 2014).

3.3.2. 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 laboratory systems. HIPE is a national database of coded discharge summaries from acute public hospitals in Ireland (O'Callaghan et al., 2012, O'Loughlin et al., 2005). 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.

3.3.3. 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). Seventy-four out of the total of 3409 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 Republic of Ireland. The first was developed by the Small Areas Health Research Unit (SAHRU) of Trinity College Dublin. They created 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 a methodology similar to Townsend and Carstairs (Townsend, 1987, Carstairs and Morris, 1989) to derive a Deprivation Score by using principal components analysis (PCA) against a weighted combination of four indicators, relating to unemployment, social class, type of housing tenure and car ownership (Kelly and Teljeur, 2013). Essentially, several 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 acute 30-day acute hospital mortality (Conway et al., 2013), admission and readmission rate incidences (Cournane et al., 2015b) and hospital costs following an emergency medical admission (McCabe et al., 2017).

The second method for assessing deprivation at a national level uses a multi-dimensional model based on 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 have been identified and chosen: Demographic Profile, Social Class Composition and Labour Market Situation are evaluated to construct the POBAL Haase Pratschke Deprivation Index (Haase and Pratschke, 2012). The methodology adopted by POBAL allows for the creation of both an Absolute Risk Index and a Relative Risk Index. Data can be assembled and presented from the street level, through a small area, to Electoral Division and larger aggregate levels such as County or Region.

Admitted patients were assigned to their designated small area population area using ArcGIS Geographic Information System software, the implementation of which is based on the well-described 'Point-in-Polygon' algorithm as outlined by (Shimrat, 1962). 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.

3.3.4. Statistical methods

Descriptive statistics were calculated for background demographic data, including means/standard deviations (SD), medians/interquartile 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 admission if there were more than one admission) with the previously described predictor variables that included age, acute Illness Severity score (Silke et al., 2010, O'Sullivan et al., 2012), the Charlson Comorbidity Index (Charlson et al., 1987), the Chronic Disabling Score (Chotirmall et al., 2014c) and Sepsis Status (Chotirmall et al., 2016a). We employed a logistic model with a robust estimate to allow for clustering; the correlation matrix thereby reflected the average dependence among the specified correlated observations (Silke et al., 2010). Logistic regression analysis identified potential mortality predictors and then tested those that proved to be significant univariate predictors ($p<0.1$ by Wald test). 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 truncated Poisson model. We used robust standard errors for the parameter estimates, as recommended by (Cameron and Trivedi, 2010). 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 (IRR). We regressed the categorization 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.

Adjusted odds ratios (OR) and 95% confidence intervals (CI) were calculated for those predictors that significantly entered the model ($p<0.10$). Statistical significance at $P<0.05$ was assumed throughout. Stata v.13.1 (Stata Corporation, College Station, Texas) statistical software was used for analysis.

3.4. Results

3.4.1. Patient Demographics (Table 3.1)

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) yrs, with the upper 10% boundary at 84.9 yrs.

Deprivation status was classified by Quintiles (Q1 low – Q5 high) at the level of the District Electoral Division. There was a total of 74 EDs in the catchment area with a population of 210,443 people, 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 III (n=5), Quintile IV (n=7) and Quintile V (n=49). The demographic characteristics (Table 3.1) are outlined with a cut point at the Q3/Q4 boundary and tabulated by Acute Illness Severity (Silke et al., 2010, O'Sullivan et al., 2012), Charlson Co-Morbidity Index (Charlson et al., 1987), Chronic Disabling Disease Score (Chotirmall et al., 2014c) and Sepsis status (Chotirmall et al., 2016b). Patients from less deprived areas (Q1-Q3) were, on average older at the time of admission, 66.1yr (46.2, 79.2) compared with the more deprived 64.8 yr (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 in 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 disadvantaged areas (higher SES) had higher Acute Illness Severity scores and higher rates of Chronic Debilitating and Respiratory Disease. 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.

3.4.2. 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 quintiles in 46% of cases, and for the 2011 comparison, absolute agreement concurred in only 42% of cases. For the 2006 Census, POBAL HP 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 HP 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 upward ranking bias of POBAL HP versus SAHRU (towards less deprivation). This resulted in high admissions incidences being allocated to lesser deprived areas compared with the SAHRU classification.

3.4.3. Admission and Readmission Incidence Rates (Fig 3.1 – Fig 3.2)

The admission incidence rate was significantly predicted by Deprivation status in the multiple variable models adjusted for the other predictive variables of Acute Illness Severity (Silke et al., 2010, O'Sullivan et al., 2012), Charlson Co-Morbidity Index (Charlson et al., 1987), Chronic Disabling Disease Score (Chotirmall et al., 2014c) and Sepsis status (Chotirmall et al., 2016a). For SAHRU, the incidence rate ratio (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 POBAL HP, using the Census data, the multiple variable model adjusted for other 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) using 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) using the 2011 census data.

The readmission incidences estimates were similarly higher (Fig 2) for the POBAL HP model compared with the SAHRU model based on the Census Deprivation ranks; however, the model predictions for the SAHRU model with the 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 in the model based on POBAL HP had IRRs of 1.32 (95% CI: 1.32, 1.33) and 1.30 (95% CI: 1.29, 1.31) for the 2006 and 2011 models, respectively.

3.4.4. <u>Modelling based on different Census (2002, 2006 and 2011 - Fig 3.3)</u>

We do not know the time frame over which environmental or socio-economic factors operate; that is, how to weigh how long the risk exposure is before the consequence is expressed as an emergency medical admission? If the duration of exposure is decades, for example, then we cannot anticipate that changing Census statistics will be accompanied by a 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 Electoral Divisions (74) by quintiles of SAHRU classification) for three consecutive Censuses, 2002, 2006 and 2011. We adjusted the data for the Dependency Ratio, Acute Illness Severity Score (Silke et al., 2010, O'Sullivan et al., 2012), the Charlson Comorbidity Index (Charlson et al., 1987), the Chronic Disabling Score (Chotirmall et al., 2014a) and Sepsis Status (Chotirmall et al., 2016a). The multi-variable 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 2002, 2006 and 2011 versions, respectively. The models were different with both 2002 and 2006 superior to 2011; there were small differences between 2002 and 2006 ($Chi2 = 88.2$: $p<0.01$).

3.5. Discussion

St James' Hospital is in an area of high deprivation (Walsh et al., 2004); our experience of 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 these can be explained by the concentration in those areas of people with adverse personal or socio-economic factors (Sloggett and Joshi, 1994). 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 (Conway et al., 2016a, Cournane et al., 2016, Cournane et al., 2015a). The rates of emergency medical admissions at our institution, when considered in absolute terms, were in line with those of the UK (Tian et al., 2012). Given the low incidence rate (absolute rate of 1.5% - 1.7% of the population will have an emergency medical admission per annum), the unit area of calculation has to be of a reasonable size; within the catchment area, there are 74 DED,'s with a median population per ED of 2845 (IQR 2020, 3399). This sample size appeared adequate to allow incidence rate calculations, to allow the influence of deprivation on acute 30-day acute hospital mortality (Conway et al., 2013), admission and readmission rate incidences (Conway et al., 2015a) and hospital costs (McCabe et al., 2017) 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 utility 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, 2012). Should one wish to move toward defining deprivation at an even smaller level (street or even individual level), particularly where a census-based deprivation index is used as a proxy for individual-level social position, then one needs Small Areas (SA's) to be standardised in size as in POBAL HP– 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, with pockets of affluence colloquially termed 'gentrification'. Over time this reflects new apartment developments as urban regeneration impacts the inner city. However, forty-nine of the 74 electoral divisions in our catchment area are in the 4th and 5th Quintiles (lowest SES) of the SAHRU distribution and demonstrate a stable relationship to 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 deprivation is shown to have a health outcome consequence, such as increasing admission and readmission rates. It is likely that socio-economic and environmental factors influence health outcomes 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. 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, HP at the District Electoral Division level, POBAL classifies areas at a higher level of SES; the transfer of classification from more to less deprived resulted in the inflation of the calculated admission incidence rate, and compression of the calculated readmission incidence rate. 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 calculations. 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. It is noteworthy that a similar phenomenon- where there is a compression in effect size as one moves from a 'close to the individual' to an area based assessment of deprivation- has been seen by a Canadian group who have looked at the effect of deprivation on life expectancy (Pampalon et al., 2009, Pampalon et al., 2010). Their work has shown that calculations based on deprivation index for individuals yield a difference in life expectancy between the least and the most deprived of 8.8 years. When the calculations are completed based on enumeration areas the difference shrinks to 3.5 years.

Interestingly a group in London (Beeknoo and Jones, 2016b, Beeknoo and Jones, 2016a) have described a blended approach that adjusts small area deprivation data to reflect the status of the larger 'super output area'. By nuancing larger area data in this way, one can more accurately describe and predict 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. This is relevant as there is no clarity in relation to the timeframe 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 is known as gentrification and is worth reflecting on when following populations over time (Hochstenbach and Boterman, 2018, Sheppard, 2012). The available evidence suggests that the societal consequences are complex but argue against the idea that the movement of the local population might be on a scale to influence overall health statistics (Ding and Hwang, 2016). Interpretation of longitudinal health service utilisation data will require careful consideration to ensure that all population segments are adequately catered for. These, of course, will reflect more remote socio-economic circumstances that incubated ill health, as revealed by the current level of clinical presentations.

3.6. Conclusion

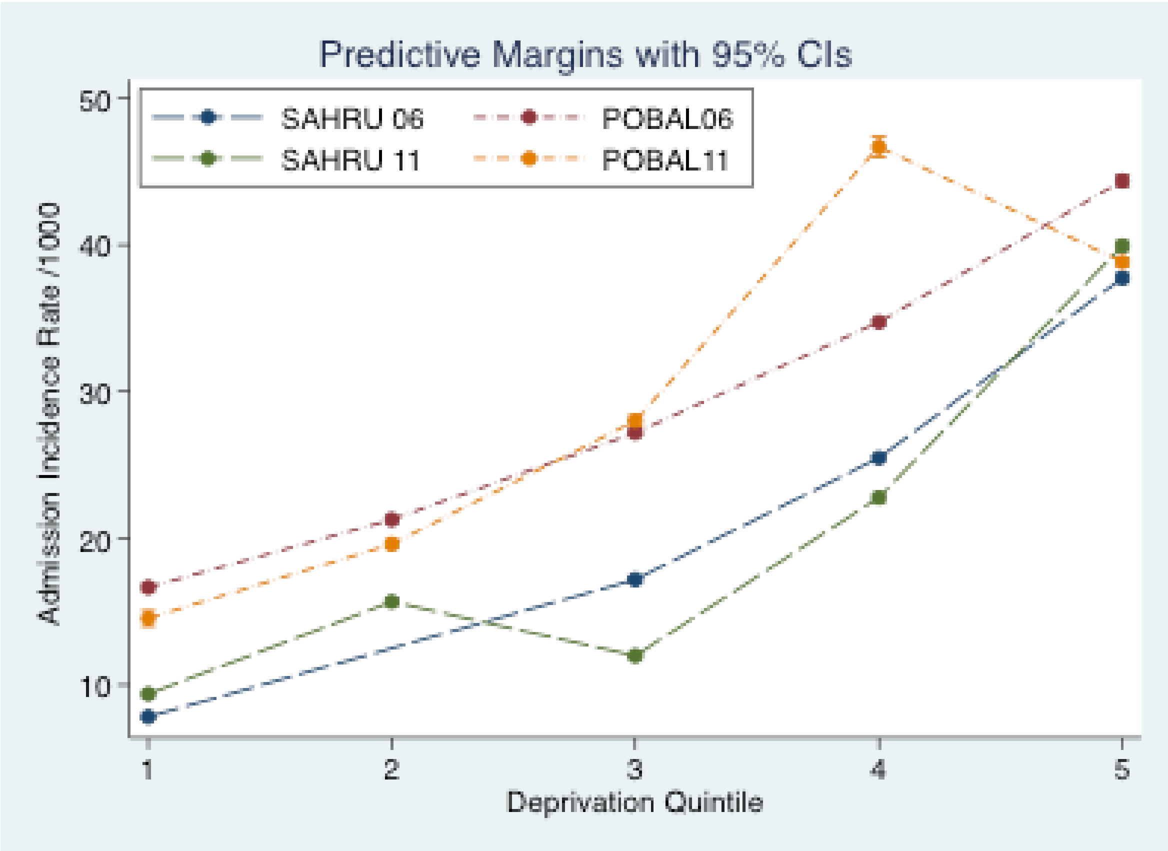
Deprivation influences hospital incidence rates for emergency medical admissions and readmissions. Instruments focusing on the very small area (individual or street level) have a utility but appear inferior in terms of representing the population risk which seem better approximated at a larger scale.

Table 3.1: Characteristics of Emergency Medical Admissions by Deprivation Status

Factor	Level	Low Deprivation	High Deprivation	p-value
N		20057	42366	
Gender	Male	10255 (51.1%)	20215 (47.7%)	<0.001
	Female	9802 (48.9%)	22151 (52.3%)	
Outcome	Alive	18953 (94.5%)	40348 (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%)	16469 (42.5%)	
Charlson Index	0	9050 (45.2%)	17446 (41.3%)	<0.001
	1	5673 (28.3%)	12646 (29.9%)	
	2	5289 (26.4%)	12178 (28.8%)	
Disabling Disease	0	2090 (10.4%)	4112 (9.7%)	<0.001
	1	4997 (24.9%)	10087 (23.8%)	
	2	5819 (29.0%)	12251 (28.9%)	
	3	4414 (22.0%)	9447 (22.3%)	
	4	2737 (13.6%)	6469 (15.3%)	
Sepsis Status	0	15053 (75.1%)	32439 (76.6%)	<0.001
	1	4275 (21.3%)	8459 (20.0%)	
	2	729 (3.6%)	1468 (3.5%)	

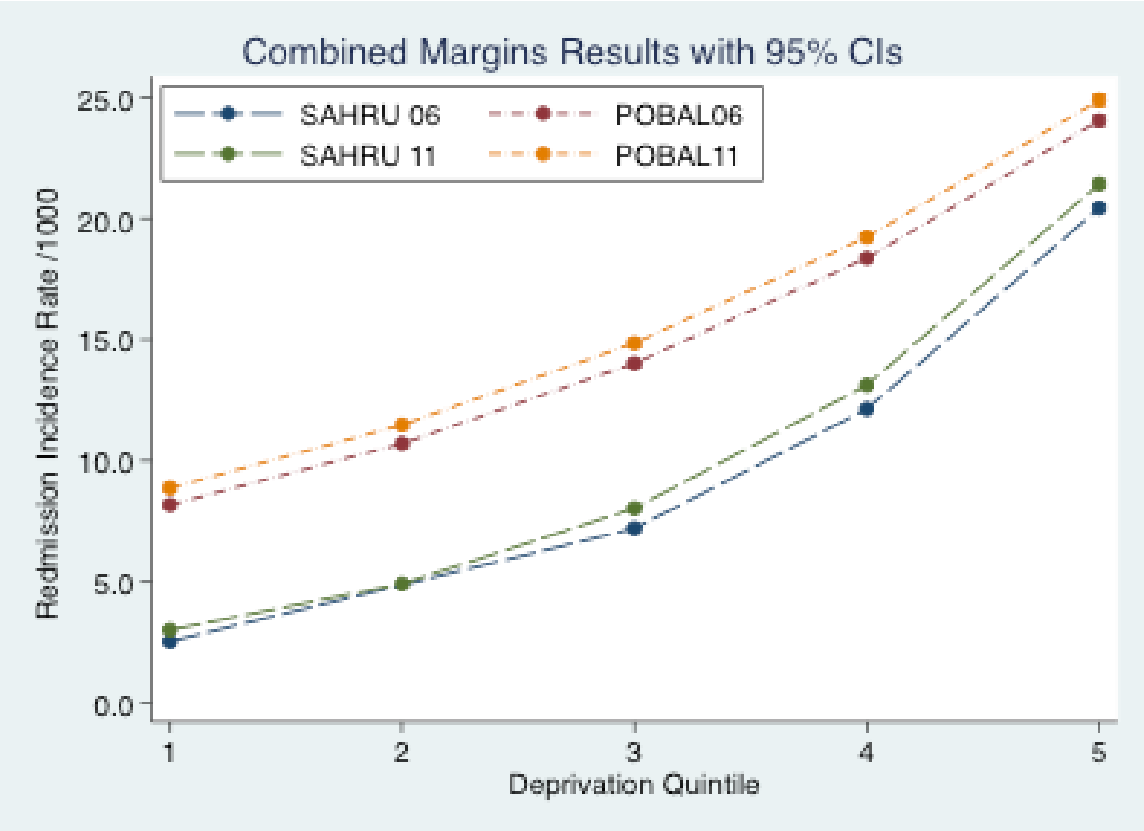
LOS: length of stay, MDC: Major disease category, IQR: Inter-Quartile Range

Figure 3.1: Relationship between Hospital Admission Rate and Deprivation Status.



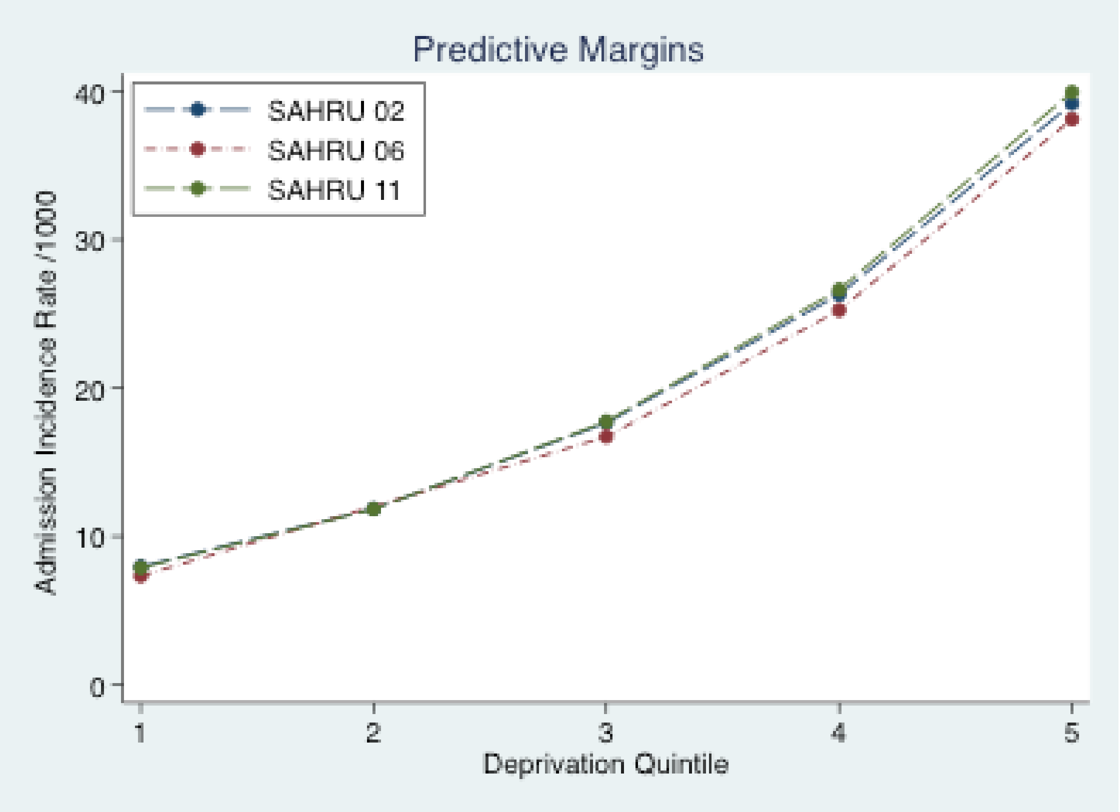
*The hospital admission incidence (rate / 1000 population) was strongly influenced by the deprivation status. The SAHRU and POBAL ranks were for catchment small areas (DED) from low (Q1) to high (Q5) deprivation. The predicted probabilities were derived from the multiple variable truncated Poisson model;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

Figure 3.2: Relationship between Hospital Readmission rate and Deprivation Status.



The hospital readmission incidence rate (number readmission/ 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 the Censuses of 2006 and 2011. Readmission rates were calculated as cumulative readmissions for each District Electoral Division /1000 population averaged over 15 years.

Figure 3.3: Comparing Predictive Modelling of Hospital Admission by Deprivation Status over time.



The model of hospital admission 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 admission rate incidence was based on the 2002 and 2006 census data.

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Chapter 4 . **Discussion**

Inequality, a widening gap between rich and poor, and the concept of successful ageing are defining features of our time. This thesis has examined the impact of socio-economic status and multi-morbidity on the health outcome of hospital admission. It has also examined whether the method of deprivation index calculation and how it estimates socio-economic status at larger or smaller population-level impacts our understanding and representation of population risk with respect to hospital admission rate.

Most noteworthy is the observation from our patient group that a younger cohort (at the time of emergency medical admission) from a low socio-economic status background has an equivalent multi-morbidity burden to the older higher socio-economic cohort, but that the disease profile is considerably different and is possibly attributable to the age difference at time of presentation. This may represent the phenotypic expression of adverse health outcomes related to differences in lifestyle as evidenced by the over-representation of respiratory and diabetes illness in the less affluent group. People from the lower socio-economic groups are presenting approximately 10 years earlier than those from more affluent areas. This raises interesting questions in relation to chronic disease management programmes and resource allocation. The SAHRU group have previously described reduced life expectancy for women (6.4 years) and men (7.5 years) between the most and least deprived areas of the country (see figure 4.1).

In addition, irrespective of which deprivation index is applied, socio-economic deprivation influences hospital incidence rates for emergency medical admissions and readmissions. Instruments focusing on the very small area (individual or street level) have a utility but appear inferior in terms of representing the population risk which seem better approximated at a larger scale. Again, the SAHRU group have also shown a gradation effect with respect to hospital admission rate versus socio-economic deprivation (see figure 4.2).

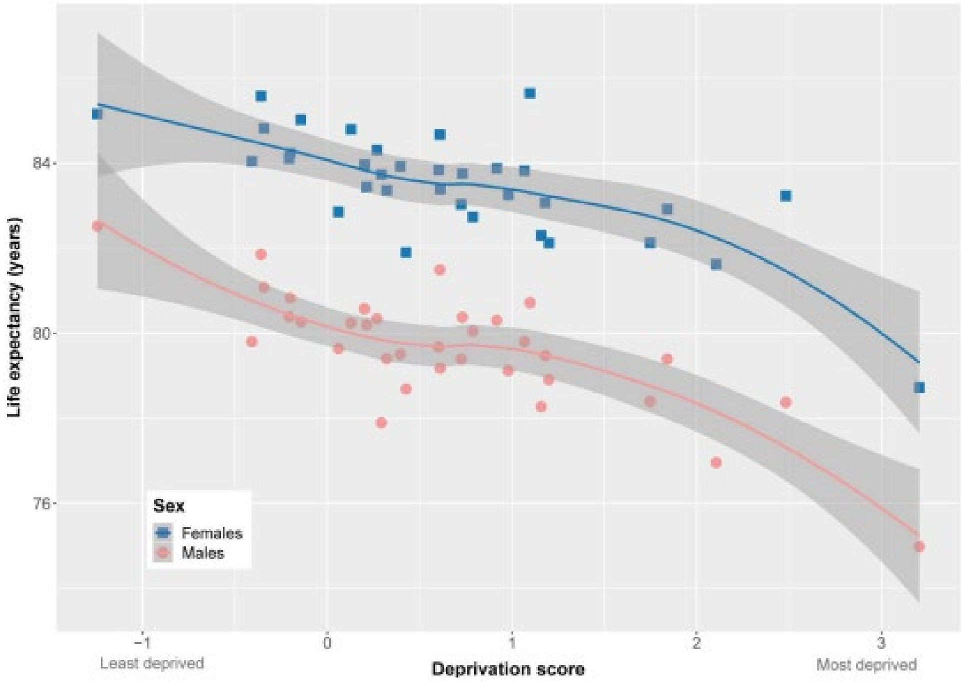

Figure 4.1: Deprivation and life expectancy by County (2016).

After (Teljeur et al., 2019)

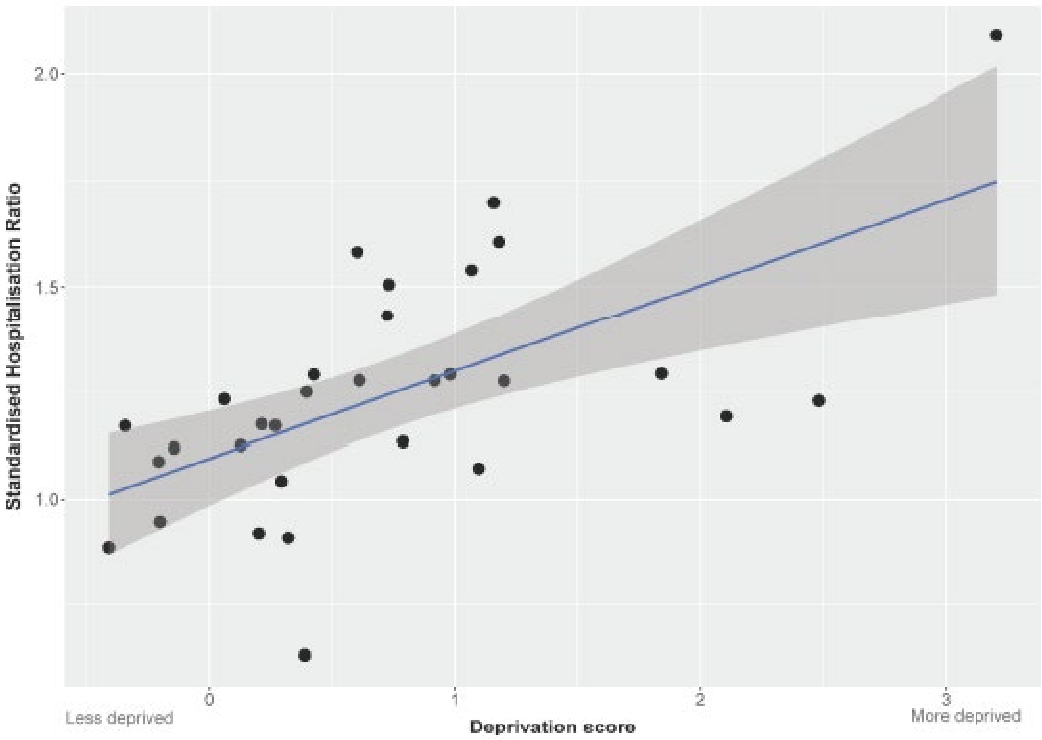

Figure 4.2: Deprivation and standardised hospitalisation ratio by county (2016).

After (Teljeur et al., 2019)

With this in mind it is worth reflecting on the Irish Government's policy direction in terms of health care delivery. The policy, Slaintecare, provides a high level roadmap to deliver service reform and universal healthcare (Burke et al., 2018). The policy has five components- population health, entitlement, integrated care, funding and implementation. The reforms, if delivered, will create a universal single tier health service where patients are treated solely on the basis of need. This will represent a significant change for the Irish population. At present 60% of the population pay for primary care visits out of personal income and up to two thirds of the population absorb the first €144 of medication cost each month before they become eligible for support. The implementation of Slaintecare has been slow but given the scale of the ambition this is not unexpected. The World health Organisation describes Universal healthcare as a system where "all individuals and communities receive the health services they need without suffering financial hardship". By definition this encompasses the full suite of essential services ranging from health promotion and prevention, through to diagnosis and treatment and extending into rehabilitation and palliative care across the life course.

The Irish Health Service Executive (HSE) has launched a Chronic Disease Management (CDM) programme as a component of the Slaintecare reforms. Initially, its focus is on the following conditions: Chronic Obstructive Pulmonary Disease, Asthma, Type 2 Diabetes Mellitus, and cardiovascular diseases, including heart failure, ischaemic heart disease and atrial fibrillation (Tandan et al., 2022). For a patient to be eligible for the CDM programme, they must be eligible for a Medical Card or a GP visit card. Interestingly, the plan for the implementation of the programme indicated that the first group to be brought under its auspices would be those over 70 years of age in 2020. They were followed by those over 65 in 2021, and then, from 2022, all adults aged 18 and over. Given the findings presented in this thesis, one could argue for a more nuanced approach to resource allocation that factors in the inequality that prevails in society. Social deprivation drives accelerated progression of chronic disease and earlier requirement for acute hospital admission. This is an arbiter that requires equal consideration to age, given the propensity for impact across a greater number of life years for those patients from less advantaged areas. Indeed, one could consider expanding the schema by (McMaughan et al., 2020) presented in the Chapter 1, to include factors such as positive health behaviours, chronic disease expression and hospital admission within the rubric of healthy ageing (see figure 4.3). In this regard the concept of proportionate universalism requires due consideration (Carey et al., 2015). From a starting point of accepting that the "hardest to reach" are often the ones we need to reach most, this approach suggests that health actions must be universal, not targeted, but with a scale and intensity that is proportionate to the level of disadvantage. The concept is seductively simple, however the authors caution against the rush to simplicity and argue that evidence must be integrated from social and welfare policy research as well as adopting a multi-level governance approach and the principle of subsidiarity (allowing individual members of a large organisation make decisions on issues that affect them, rather than leaving those decisions to be made by the whole group). There are good examples of grass roots affirmative action in areas of disadvantage. The Deep End Project (Butler et al., 2022, Dhanani and Blane, 2023) originated in Scotland and has established in Dublin. It's core mission is to create a focal point of interested and committed clinicians working in areas of social disadvantage to lift the delivery of healthcare and improve health outcomes. For example, they have described the phenomenon of '*missingness*' which outlines how people who have a history of underusing and missing GP appointments are higher users of hospital outpatient and inpatient services (Williamson et al., 2021). The core problem that Deep End wish to address is the x2.5 increased mortality rate that the socio-economically deprived experience relative to those in more affluent areas. The nett survival disadvantage is in the order of 7-years.

A limitation of the work for this thesis is that it was completed in a single centre. This limits generalisability. However, due to serendipity or otherwise, it does disclose a narrative relating to those from more disadvantaged communities in Dublin. It is also noteworthy that the data was captured routinely as part of clinical practice. The source data, aggregated and anonymised for administrative return to the National Hospital Inpatient Enquiry (HIPE) system, represented the backbone of the data source. Our ability to accurately code patient episodes of care leans into the work underpinning the concept of standard clinical terminologies. These are more commonly known as Coding Systems. The most commonly used system is the International Classification of Diseases (WHO, 2016). This is now in its tenth iteration (ICD-10) and soon to launch its eleventh. The coding process is currently done manually and can be based on diagnoses, symptoms, abnormal laboratory findings, external causes of morbidity, injuries/ poisoning, and factors (such as homelessness) influencing health status. It is divided into 21 chapters. With the advent of machine learning, it is possible that ICD coding may be automated in future (Shi et al., 2017). Whilst ICD coding is useful and robust, there are alternate coding systems that allow for a deeper and richer description of the clinical problems and associated environmental and social issues that may be contributing to an individual patient's problem set at the time of their review. One such system is SNOMED- the Systematised Nomenclature of Medicine (SNOMED, 2003).

We were able to link this data over an extended period of time to changes in our catchment population demographic via census data. It is worth noting that the design of the POBAL HP Deprivation Index will allow for a more robust comparison between groups over time. In the real world, there is also the possibility of social mobility (Moving between socio-economic groups) and the reality that individuals can move between geographic locations. Thus, it would be interesting and useful to explore how one might track and record the amount of time people spend in each area, at what stage of life, and assess how that impacts health service utilisation. This may well become possible with the phased implementation of the Individual Health Identifier system that has been commenced by the HSE. It will be interesting to see if this unique identifier can be harnessed to allow research to proceed in examining how socio-economic 'exposures' relate to health outcomes. The purpose of the IHI is to facilitate interoperability between Information and Computer Technology (ICT) systems; as such, it will involve transfers of data between different ICT systems. The lawful basis for this data transfer is the Health Identifiers Act 2014, Section 7(1), Section 10(2) and Section 10(4), and the Health Act 2004 Section 7. The purpose of these data transfers is to facilitate the roll-out of the IHI on a national level in line with Sláintecare Strategic Action 10, and specifically Project 6 of the Sláintecare Implementation Plan 2021-2027 (Slaintecare, 2017).

One could argue that joining these strands- leveraging off the potential of routinely collected clinical data; linking with census and other administrative data and having a better of view of how the individual behaves within the collective- will enable us to move closer to the ideal of proportionate universalism. Haase and Pratschke have argued in favour of evidence-based resource allocation on the basis of differential risk exposure by virtue of socio-economic position (see figure 4.4). In theory, this should result in more efficient public services as well as achieving greater social inclusion. It makes sense that this should be a key deliverable in a system that strives to embrace the concept of evidence-based design.

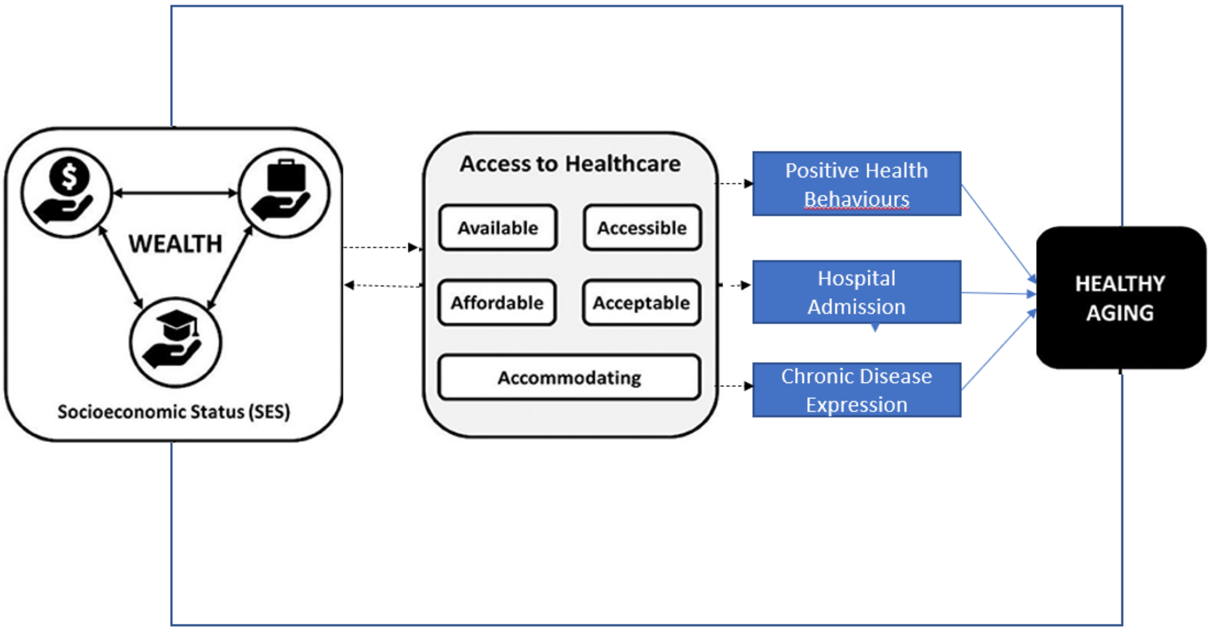

Figure 4.3: Link between SES & Healthy Ageing (based on (McMaughan et al., 2020)).

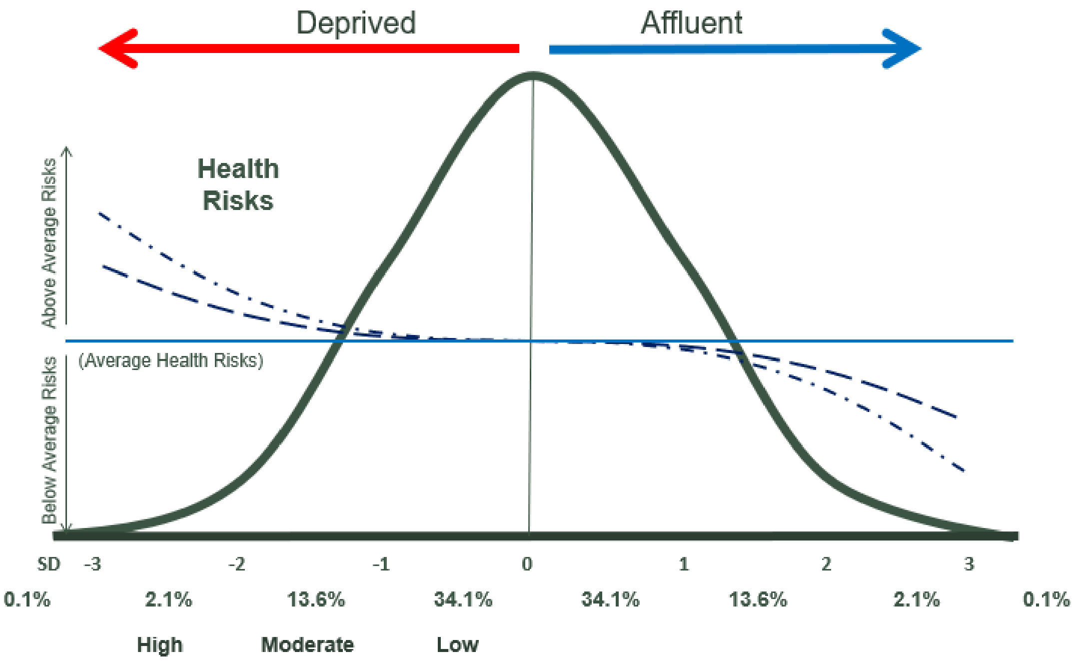

Figure 4.4: Risk versus deprivation. (after (Haase et al., 2014))

Future Work:

1. At present, we are only capable of using hospital-based outcome measures such as in-hospital mortality, length-of-stay, readmission rate and so on. It would be useful to access national mortality registry data to assess out-of-hospital death as an outcome measure. This will allow us to interrogate if there are downstream implications for those from socio-economic groups with multi-morbidity who experience their first hospital admission earlier than those from more affluent areas.
2. With the roll-out of the National Individual Health Identifier, it would be interesting to investigate the full repertoire of health services that are being utilised by people across social groups. In addition, it would be useful to identify the split in service delivery across the public: private patient boundary by socioeconomic group.
3. Identify national and international collaborators working in the area of health outcomes for acute medical patients.

Chapter 5 . **References**

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Chapter 6 . Appendices

6.1. Appendix 1: Socio-economic Status and Multi-morbidity- Fact or Fiction? Acute Medicine 2019; 18(2): 64-70.

Original Articles

Socio-Economic Status and Multi-morbidity – Fact or Fiction?

D Byrne, S Cournane, R Conway, D O'Riordan & B Silke

Abstract

Background: *Areas of low socio-economic status (SES) have a disproportionate number of emergency medical admissions; we quantitate the profile of multi-morbidity related to SES.*

Methods: *We developed a logistic multiple variable regression model, based on over 15 years of hospital data, to examine the effect of socio-demography on hospital outcomes.*

Results: *Admissions from low SES cohort were a decade younger, and had a shorter hospital stay, and lower 30-day episode mortality outcome. The number of morbidities was equivalent between groups, but the more disadvantaged were more likely to have a respiratory diagnosis or diabetes.*

Conclusion: *Low SES emergency admissions present > 10 yr. earlier than the high SES population; their equivalent multi-morbidity, despite a lower age, could reflect accelerated disease progression.*

Keywords

Demographics, Morbidity, Socio-Economic Status (SES)

Key points

- Patients from more disadvantaged areas present a decade earlier than those from higher socioeconomic groups.
- There is an excess of respiratory illness and diabetes amongst the disadvantaged cohorts.
- Further study of the lifestyle correlates and patterns of chronic disease management are merited.

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Introduction

Morbidity broadly speaking may be considered to be present when an individual possesses symptoms that indicate ill-health or the presence of disease. Morbidity may also represent the complications or undesirable outcomes of therapy or the rate of illness in a select population group.[1] It is generally accepted that the 'poor', as in persons from more deprived backgrounds, tend to consume more hospital resources.[2] This may be because low socioeconomic status (SES) is associated with multi-morbidity; onset of multimorbidity was found to occur 10–15 years earlier in people living in the most deprived compared with the most affluent areas.[3] Our hospital catchment area contains many small areas characterised by a high deprivation status.[4] However, as practicing clinicians we have no clear view as to whether individuals with different SES backgrounds have a different morbidity profile at the time of an emergency medical presentation.

Instruments to assess morbidity typically employ administrative data such as hospital discharge codes to construct a risk profile; the assessment can be single code evaluation (a single hospitalisation with limited codes) or more complex (inpatient and out-patient encounters and many codes screened).[4] Previous work, such as that of Barnett et al,[3] identified 40 morbidities and were informed by a systematic review of multimorbidity measures[6] – the Quality and Outcomes Framework of the UK General Practice contract, and health service planning by NHS Scotland. Apart from data sources that might be specific to the United Kingdom, a Canadian group proposed an alternative approach using validated algorithms that used ICD9 CM/ICD-10 to ascertain the presence or absence of 40 morbidities.[7] From these they identified a panel of 30 chronic conditions that that could potentially facilitate the study and surveillance of multimorbidity.[8] It is reasonable to assume that, at steady state, a given rate of population comorbidity will translate into a proportionate rate of emergency hospitalisation; comparison between the documented comorbidities from different SES populations might then reasonably permit inference regarding the prevalence or comorbidity within these different SES small areas.

This study therefore investigates whether our catchment area population, heavily weighted to low SES status, possesses a disproportionate level of multi-morbidity and whether this can be determined from the data captured routinely using the hospital administrative systems. We have examined the last 16 years of acute medical admissions (2002-2017) comprising 106,586 episodes of care at St James' Hospital, Dublin in order to investigate the relationship between the multimorbidity in emergency medical admissions related to low or high socio-economic status.

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.[7,8] As a city centre hospital St James's admits persons resident elsewhere but working in the capital in addition to visitors to Dublin who became acutely ill. The number of emergency medical admissions resident in the catchment area was 74.5%; this compares with a figure of 59% for ED presentations where the social influences on emergency department visitations on two London hospitals have been examined.[9]

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 laboratory systems. HIPE is a national database of coded discharge summaries from acute public hospitals in Ireland.[10, 11] 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.

Multi-morbidity Instrument

Hospital HIPE codes[10, 11] were interrogated to construct a measure of multi-morbidity. To devise the score, we searched ICD9 hospital episode discharge codes (back-mapping ICD10 codes to ICD9 as appropriate) based on the definition proposed by the US Department of Health and Human Services for chronic physical or mental health disorders, that limit people 'in activities that they generally would be expected to be able to perform'. These ICD codes were similar to those proposed by the Canadian group for multi-morbidity[5] and the work of Quan;[12,13] they were grouped by system into the following ten groups: (i) cardiovascular, (ii) respiratory, (iii) neurological, (iv) gastrointestinal, (v) diabetes, (vi) renal, (vii) neoplastic disease, (viii) others (including rheumatological disabilities), (ix) ventilatory assistance required and (x) transfusion requirement. We have previously detailed the ICD9 codes utilized, based on the definition proposed by the US Department of Health and Human Services, as a supplementary Table.[14] In addition, we searched other hospital databases for evidence of diabetes (Diamond database), respiratory insufficiency (FEV1 < 2 L data pulmonary function laboratory), troponin status (high sensitivity troponin > 25 ng/L),[15] low albumin (<35 G/dL) and anaemia (haemoglobin levels < 10 G/dL) or chronic renal insufficiency - MDRD < 60 mL/min*1.73 m^2.[16] The 'morbidity score' for each individual's clinical episode during the study, was weighted by its relative importance against the 30-day mortality outcome in the multiple variable regression analysis. This study had no interventional component, used anonymised routinely collected data, complied with data protection legislation and was undertaken with the approval of hospital authorities, hence did not require approval from our institutional ethics committee.

Deprivation Instrument

The Republic of Ireland census (Central Statistical Office) 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). Deprivation metrics have been determined by the Small Areas Health Research Unit (SAHRU) of Trinity College Dublin using methodology similar to Townsend[17] and Carstairs[18] to derive a Deprivation Score using principle components analysis (PCA); a weighted combination of four indicators, relating to unemployment, social class, type of housing tenure and car ownership.[19] We have previously demonstrated the utility of the SAHRU classification of Deprivation in terms of predicting acute 30-day acute hospital mortality,[20] admission and readmission rate incidence[21] and hospital costs following an emergency medical admission.[22] The assignment of patients to small area population area used the ArcGIS Geographic Information System software implementation of the well-known Point-in-Polygon algorithm as outlined by Shimrat.[23]

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

Table 1. Characteristics of Emergency Medical Admission Episodes by SES

	High SES (N = 6773)	Low SES (N = 61928)	p-value
Age (yr.)			
Mean (SD)	71.43 (16.45)	62.59 (20.16)	<0.001
Median (Q1, Q3)	77.5 (61.8, 84.8)	66.3 (47.1, 79.3)	
Length Stay (day)			
Mean (SD)	17.87 (38.36)	15.29 (34.98)	<0.001
Median (Q1, Q3)	6.8 (2.9, 16.3)	6.1 (2.7, 13.6)	
Gender			
Male	3032 (44.8%)	28708 (49.0%)	<0.001
Female	3741 (55.2%)	29917 (51.0%)	
30-day Hospital Mortality			
Alive	6294 (92.9%)	55344 (94.4%)	<0.001
Dead	479 (7.1%)	3281 (5.6%)	
Morbidity Score			
< 6	1391 (28.1%)	13216 (31.9%)	<0.001
>=6 < 8	1317 (26.6%)	11266 (27.2%)	
>=8 < 12	1762 (35.6%)	13303 (32.1%)	
>=12 < 20	483 (9.8%)	3617 (8.7%)	
Charlson Index			
0	3146 (46.8%)	24687 (42.2%)	<0.001
1	1937 (28.8%)	18319 (31.3%)	
2	1678 (24.9%)	15474 (26.5%)	
Sepsis Group			
1	5089 (75.1%)	43928 (74.9%)	0.924
2	1395 (20.6%)	12195 (20.8%)	
3	289 (4.3%)	2502 (4.3%)	

chi-square tests. For count data (hospital LOS and readmissions), 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.[24] 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 (IRR).

We adjusted the prediction of outcome (30-day in-hospital mortality) for known predictor variables that included multi-morbidity score, the Deprivation Index, age group (5 yr. groups), single parent status and higher educational attainment status (higher education > 18 yr.). 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.[25] Logistic regression analysis identified potential mortality predictors and then tested those that proved to be significant univariate predictors (p<0.1 by Wald test) to ensure that the model included all variables with predictive power. We used the margins command in Stata 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 multiple variable model (logistic or 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.

Adjusted odds ratios (OR) and 95% confidence intervals (CI) were calculated for those predictors that significantly entered the model (p<0.10). Statistical significance at P<0.05 was assumed throughout. Stata v.15 (Stata Corporation, College Station, Texas) statistical software was used for analysis.

Results

Patient Demographics

During the 16-year study period (2002-2017), there were a total of 106,586 episodes of medical emergencies in 54,928 unique patients admitted through the Emergency Department. These episodes represented all emergency medical admissions, including patients admitted directly into the Intensive Care Unit or High Dependency Unit.

The demographic characteristics (Table 1) are outlined with a division of 'low' or 'high' socio-economic status (lower/higher cut at Deprivation Quintile 3 – i.e. Q4/5 low SES) at presentation and tabulated (to allow group comparisons) by our Co-morbidity Score, Charlson Index[26] and Sepsis status.[27] Admissions with a lower SES were younger 66.3 yr. (IQR: 47.1, 79.5) vs. 77.5 yr. (61.8, 84.8) and had a shorter hospital stay 6.1 day (2.7, 13.6) vs. 6.8 day (2.9, 16.3) and a lower 30-day episode mortality (5.6% vs. 7.1%) outcome. These younger admissions from the low SES catchment area were less likely to have a higher Co-Morbidity Scores (≥ 8 points – 40.9% vs. 45.4%), Charlson Index (Grade

2 – 26.5% vs. 24.8%) but had similar sepsis scores. From an overall clinically perspective, one therefore could regard the groups as essentially equivalent in risk profile, albeit with an age difference of approximately one decade.

Comparison of Disease Profiles (Table II)

The disease profile showed distinct differences related to the SES of emergency admissions. Emergency admissions with primary diagnoses of respiratory (32.8% vs. 22.1%) or mental disorders (16.0% vs. 9.9%) occurred with a high frequency in admissions from a lower SES background. Cardiovascular disease was somewhat higher in those from lower SES areas (9.6% vs. 8.2%). Diabetes was much more evident in the lower SES areas (11.8% vs. 8.8%). The overall rate of admission for alcohol related or with a detoxification classification was not that high, but again very different between low and high SES area (4.3% vs. 1.6%). Gastro-intestinal disorders were more evident within the low SES admitted cohort (26.7% vs. 23.3%). In contrast, disorders related to cognition or behaviour related were more frequent in the older population (10.4% vs. 7.6%) admitted from the higher SES small areas.

Multi-morbidity construct and Socio-Economic Status (Table III)

We regressed the significant mortality predictors against SES to test the dependency of these predictors and the small area of residence. Persons living in areas with low SES, were more likely to have respiratory disease – OR 1.39 (95% CI: 1.29, 1.49) and to require ventilation – 1.27 (95% CI: 1.03, 1.56) and to be admitted with Diabetes – 1.54 (95% CI: 1.37, 1.75) or Gastro-intestinal disease – 1.35 (95% CI: 1.24, 1.49). They were less likely to have a Neurological – 0.66 (95% CI: 0.61, 0.71), Cardiovascular – 0.79 (95% CI: 0.73, 0.85) or renal – 0.59 (95% CI: 0.55, 0.64) admission or to require a blood transfusion – 0.81 (95% CI: 0.65, 1.00).

Table II. Disease Profile of Emergency Medical Admission Episodes by SES

	High SES (N = 6773)	Low SES (N = 61926)	p-value
Cardiovascular			
0	6216 (91.8%)	53020 (90.4%)	<0.001
1	557 (8.2%)	5605 (9.6%)	
Respiratory			
0	5279 (77.9%)	41598 (67.2%)	<0.001
1	1494 (22.1%)	20330 (32.8%)	
Mental Disorder			
0	6103 (90.1%)	49260 (84.0%)	<0.001
1	670 (9.9%)	9365 (16.0%)	
Alcohol Related			
0	6665 (98.4%)	56098 (95.7%)	<0.001
1	108 (1.6%)	2527 (4.3%)	
Skin Disorder			
0	6545 (96.6%)	56130 (95.7%)	0.001
1	228 (3.4%)	2485 (4.3%)	
Gastro-Intestinal			
0	5192 (76.7%)	45332 (73.3%)	<0.001
1	1581 (23.3%)	16536 (26.7%)	
Diabetes			
0	6160 (91.2%)	51604 (88.2%)	<0.001
1	597 (8.8%)	6876 (11.8%)	
Cognitive/Behaviour			
0	6071 (89.6%)	54154 (92.4%)	<0.001
1	702 (10.4%)	4471 (7.6%)	

Table III. Multivariable Fractional Polynomial Regression of by low SES status

Variable	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Cardiovascular	0.79	0.03	-4.0	0.00	0.73	0.85
Respiratory	1.39	0.05	8.7	0.00	1.29	1.49
Neurological	0.66	0.02	-11.0	0.00	0.61	0.71
Gastro-Intestinal	1.35	0.06	6.4	0.00	1.24	1.49
Diabetes	1.54	0.10	6.9	0.00	1.37	1.75
Renal	0.59	0.02	-14.6	0.00	0.55	0.64
Neoplasm	0.94	0.06	-0.9	0.34	0.82	1.07
Sepsis	0.98	0.04	-0.6	0.54	0.90	1.06
Others	0.95	0.04	-1.4	0.17	0.87	1.02
Ventilation	1.27	0.14	2.2	0.03	1.03	1.56
Transfusion	0.81	0.09	-1.9	0.05	0.65	1.00
_cons	32.63	1.50	75.8	0.00	29.62	35.71

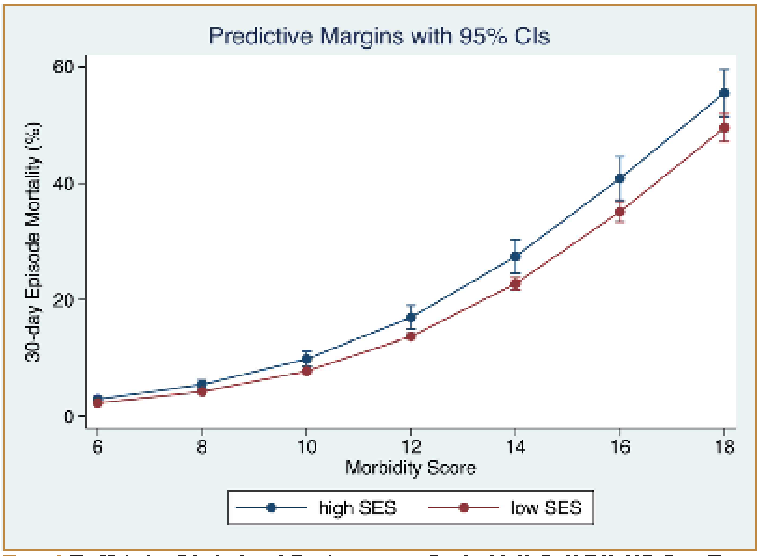

Figure 1. The 30-day hospital episode mortality outcome was non-linearly related to the Multi-Morbidity Score. The predicted probabilities were derived from the multiple variable logistic model; the effect is plotted based on the latter prediction. The older high SES group had a higher mortality predicted at any given morbidity level but the overall trend of mortality / morbidity relationship was similar

There was no difference in presentations related to sepsis, neoplasm or other assorted disorders.

Discussion

Key Findings

These data demonstrate that persons ordinarily resident in disadvantaged small areas are admitted with an emergency medical condition more than a decade earlier compared with persons resident in more affluent localities. However broadly speaking, admissions irrespective of socio-economic status appeared to have comparable multi-morbidity at time of admission – as determined either from the absolute number of disease systems or the weighted score of morbidity based on outcomes. That is to say, we found that the overall number of morbidities (median 3; (IQR 2,4) and the attributed weighted score (median 6.0; (IQR 3.8, 8.6) were similar between low and high SES admission cohorts. However, that does not imply that there were not significant differences in disease profiles and resultant consequences between the low and high SES cohorts. Low SES presentations had more respiratory (OR 1.39), diabetes (OR 1.54) and gastro-intestinal disease (1.35) but less neurological (0.66), cardiovascular (0.79) and renal (0.59) admissions and less transfusion requirement – 0.81 (95% CI: 0.65, 1.00); low SES also required more ventilatory intervention (OR 1.27).

Limitations

In order to screen for morbidity, we used the classification system proposed by the US Department of Health and Human Services for chronic physical or mental health disorders, and further screened ICD10 HIPE hospital discharge codes. We were restricted in data analysis for two reasons. Firstly Ireland used ICD-10-CM discharge coding from 2005 and our search algorithms could only interrogate this source rather than the International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) used up to this point. Second, we can only compute accurate population admission incidence rates for those resident within the hospital catchment area; as a city centre hospital (with a large transient population of workers resident outside the area and visitors) only approximately 74.5% of emergency admissions resided within the catchment area. This compares with a figure of 59%

for ED presentations where the social influences on emergency department visitations on two London hospitals have been examined.[7]

Interpretation

Overall the number of morbidities (median 3; (IQR 2,4) and the attributed weighted score (median 6.0; (IQR 3.2, 8.6) was similar between low and high SES admission cohorts. The number of morbid conditions by SES area of residence was marginal (F = 5.8, =0.02) contrasting with the much higher weighted score (F = 24.5, P<0.001) suggesting that low SES areas of residence may not necessarily have more multi-morbidity by count but that it was overrepresented with higher risk categories. Of course as age has an important influence the decade age difference between the admitted cohorts from the low and high SES areas has to be remembered.

These multi-morbidities strongly correlated with all outcomes including 30-day hospital mortality, hospital LOS and future readmissions; the odds ratios for 30-day hospital mortality were more than two fold for 6 of 11 predictive parameters, more than threefold for two and more than fivefold for one. Overall the persons from the higher SES cohort were at higher risk and had worse 30-day mortality outcomes at any given morbidity score level (Fig 1). Individuals manifesting multi-morbidities typically have a lower quality of life, and higher degrees of disability, psychological distress, risk of mortality, and utilisation of health (and social) services – than if one considers their chronic conditions in isolation or for individuals with a single chronic condition.[28] In terms of addressing the fundamental question as to how the low SES population have an emergency medical admission a full decade earlier that their better off peers; it is a conundrum as it could be due to exposure to risk from an earlier age or a higher burden of total exposure over time.

Generalisability

This is a single centre retrospective study from a relatively deprived urban centre. This limits generalisability. For context, previous estimates of morbidity within populations was based on surveys such as Taurelli et al.[4] who found that approximately one-quarter of the surveyed population (inpatients and outpatient claims data) had multi-morbidity (2 or more conditions) and 12% three or more conditions. The prevalence of 26% appeared similar to the results of Barnett.[3] Our figures of 84% overall are quite different for an emergency admitted medical population – perhaps this shows the limitations of administrative data based on hospital discharge codes with consistent underestimates of the presence of comorbidity.[29]

It is also generally agreed that multi-morbidity rises with age – in the Basque region two administrative databases suggested that multi-morbidity was higher in regions of low socio-economic circumstances.[30] The data of Barnett et al indicate that although 23.2% of the population were multimorbid and increased with age, the absolute number of people with multimorbidity was higher in those younger than 65 years. Other age- and sex-standardised estimated prevalence rates of multimorbidity was 19.0% in the general population but of those with multimorbidity, 70.2% were aged less than 65 years.[31] Our data, related to 3 age based cohorts (< 50 yr., >= 50 & < 70 yr.), indicated that for the admitted population of medical emergencies multi-morbidity was present in 67.8%, 88.2% and 93.5% of these respective cohorts.

The issue being investigated in the present work was whether the differences between the disadvantaged and better off populations could be attributed to a discrepancy in multi-morbidity between these populations rather than other social or economic issues. Our data suggests however that most emergency medical admissions to acute hospital do have a physical rather than mental component but that certain entities such as respiratory, gastro-intestinal, diabetic and alcohol related are over expressed and are a manifestation of social or behavioural influences on life style.

Conclusion

The overall conclusions is that a younger cohort (at time of emergency medical admission), from low SES background have equivalent multi-comorbidity status to the older higher SES cohort, but that the disease profile is considerably different – possibly attributable to the age difference at time of presentation. This may represent the phenotypic expression of adverse health outcomes related to differences in lifestyle as evidenced by the over-representation of respiratory and diabetes illness in the less affluent group.

Conflict of Interest

The authors declare that they have no conflict of interest regarding this publication.

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6.2. Appendix 2: Admission and Readmission rate incidences from deprived areas- impact of a classical or multidimensional model. Irish Journal of Medical Science 2019; 188: 303- 310.

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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 incidence [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 ArcGIS 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 (95.1%)	<0.001
	Died	1104 (5.5%)	2018 (4.8%)	
Age, median (IQR)		65.8 (43.6, 79.5)	63.2 (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	9058 (45.2%)	17,446 (41.3%)	<0.001
	1	5673 (28.3%)	12,644 (29.9%)	
	2	5289 (26.4%)	12,178 (28.8%)	
Disabling disease	0	2096 (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

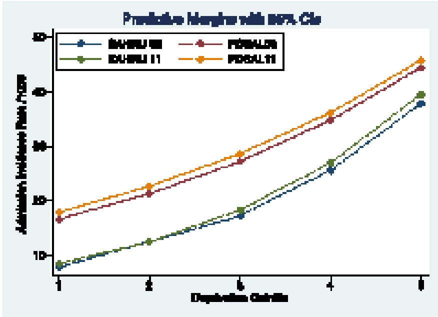

Fig. 1 The hospital admission incidence (rate/1000 population) was strongly influenced by the deprivation status. The SAHRU and POBAL ranks were for catchment small areas (DED) from low Q1 to high Q5 deprivation. The predicted probabilities were derived from the multiple variable truncated Poisson model; 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 ($\chi^2 = 88.2$; $p < 0.01$).

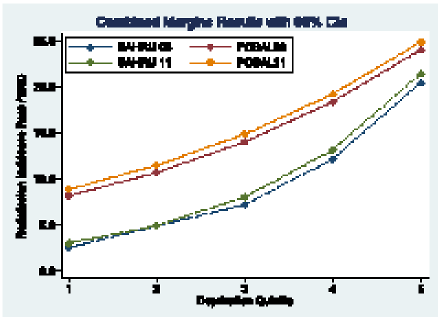

Fig. 2 The hospital readmission incidence (rate/1000 population) was strongly influenced by the deprivation status. The SAHRU and POBAL ranks were for catchment small areas from low Q1 to high Q5 deprivation. Data was from two censuses in 2006 and 2011. Readmission rates were cumulative readmissions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

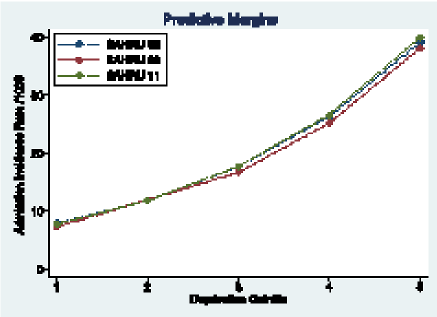

Fig. 3 The model of hospital readmission incidence (rate/1000 population) was compared over three consecutive censuses—2002, 2006 and 2011. The SAHRU ranks were for catchment small areas from low Q1 to high Q5 deprivation. The most consistent and reliable statistical model for the readmission rate incidence 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 these 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 licensed 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 comorbidities 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, Beckman 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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6.3. Appendix 3: The 2016 Pobal HP Deprivation Index for Small Areas (SA) by Haase & Pratschke (https://www.pobal.ie/app/uploads/2018/06/The-2016-Pobal-HP-Deprivation-Index-Introduction-07.pdf)

The 2016 Pobal HP Deprivation Index for Small Areas (SA)

Introduction and Reference Tables

Trutz Haase
Jonathan Pratschke

September 2017

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1 How is the 2016 Pobal HP Deprivation Index constructed?

Most deprivation indices are based on a factor analytical approach which reduces a larger number of indicators to a smaller number of underlying dimensions, factors or components. This approach is taken a step further in the Pobal HP Deprivation Index: rather than leaving the dimensions to be defined by data-driven techniques, the authors develop 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.**

Demographic Profile is first and foremost a measure of rural affluence/deprivation. Whilst long-term adverse labour market conditions tend to manifest themselves in urban areas in the form of unemployment blackspots, in rural areas the result is typically agricultural underemployment and/or emigration. Emigration from deprived rural areas is also, and increasingly, the result of a mismatch between education, skill levels and expectations, on the one hand, and available job opportunities, on the other. Emigration is socially selective, being concentrated amongst core working-age cohorts and those with post-secondary education, leaving behind communities with a disproportionate concentration of economically-dependent individuals as well as those with lower levels of education. Sustained emigration leads to an erosion of the local labour force, a decreased attractiveness for commercial and industrial investment and, ultimately, a decline in the availability of services.

Demographic Profile is measured by six indicators:

- the percentage change in population over the previous five years (positive association)
- the percentage of population aged under 15 or over 64 years of age (negative association)
- the percentage of population with a primary school education only (negative association)
- the percentage of population with a third level education (positive association)
- the percentage of households with children aged under 15 years and headed by a single parent (positive association)
- the mean number of persons per room (positive association)

Social Class Composition is of equal relevance to both urban and rural areas. Social class background has a considerable impact in many areas of life, including educational achievements, health, housing, crime and economic status. Furthermore, social class is relatively stable over time and constitutes a key factor in the inter-generational transmission of economic, cultural and social assets. Areas with a weak social class profile tend to have higher unemployment rates, are more vulnerable to the effects of economic restructuring and recession and are more likely to experience low pay, poor working conditions as well as poor housing and social environments.

Social Class Composition is measured by five indicators:

- the percentage of population with a primary school education only (negative association)
- the percentage of population with a third level education (positive association)
- the percentage of households headed by professionals or managerial and technical employees, including farmers with 100 acres or more (positive association)
- the percentage of households headed by semi-skilled or unskilled manual workers, including farmers with less than 30 acres (negative association)
- the mean number of persons per room (negative association)

Labour Market Situation is predominantly, but not exclusively, an urban measure. Unemployment and long-term unemployment remain the principal causes of disadvantage at national level and are responsible for the most concentrated forms of multiple disadvantage found in urban areas. In addition to the economic hardship that results from the lack of paid employment, young people living in areas with particularly high unemployment rates frequently lack positive role models. A further expression of social and economic hardship in urban unemployment blackspots is the large proportion of young families headed by a single parent.

Labour Market Situation is measured by three indicators:

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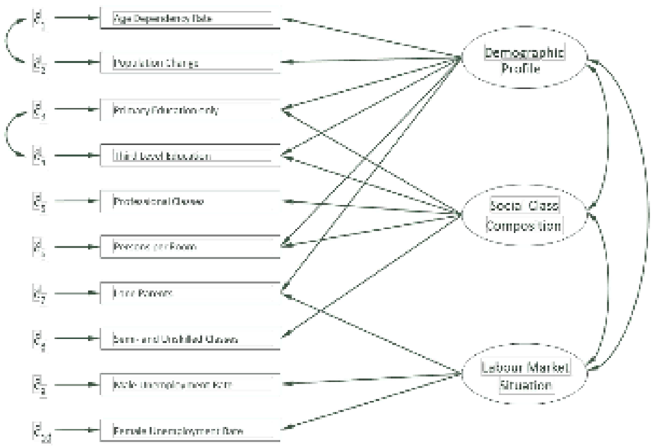
Labour Market Situation is measured by three indicators:

- the percentage of households with children aged under 15 years and headed by a single parent (negative association)
- the male unemployment rate (negative association)
- the female unemployment rate (negative association)

Figure 2: Basic Model of the Pobal HP Deprivation Index



Each dimension is calculated in the same way for each census wave and then combined to form an **Absolute Index Score** and **Relative Index Score**. The **Absolute Index Scores** have a mean of zero and a standard deviation of ten in 2006, with varying means and standard deviations in 2011 and 2016 that reflect the underlying trends.

The **Relative Index Score** is specific to a given census wave, and does not capture trends over time. By removing the national trend from the index scores, this index highlights differences in their relative values. The standard deviation is set to ten for each wave, so that the Relative Index Scores provide a standardised measurement of relative affluence and deprivation.

2 Interpreting the 2016 Pobal HP Deprivation Index Data

What is the difference between the Absolute and Relative HP Index Score?

For each census wave, the Pobal HP Deprivation Index comprises an absolute and a relative score. The Absolute Index Score measures the affluence/deprivation of each small area on a single scale which is fixed across all waves and has a mean of zero and standard deviation of ten for 2006 only. The Absolute HP Deprivation Scores for 2011 and 2016 are constructed using the same measurement scale, which means that they reflect changes in the national economy. For example, if there is economic growth between two census waves, we would expect the deprivation scores to reflect the resulting increase in affluence. Table 1 shows that the mean of the Absolute HP Deprivation scores declined from 0.0 in 2006 to -6.6 in 2011. Thus, in 2011, the SAs had scores which were, on average, 6.6 points lower than in 2006, reflecting the catastrophic effects of the 2008 recession. By comparing the mean of the absolute HP Deprivation Index scores, we can say that between 2006 and 2011, the mean of the Absolute HP Deprivation Index scores declined by exactly two-thirds (0.66) of one standard deviation, or 6.6 points on the HP Deprivation scale).

However, most users of the Pobal HP Deprivation Index are less interested in the performance of their area over the past two or three census waves, but want to know how it relates to all other areas at that point in time, and by using the latest census data. This information is provided by the 2016 Relative Pobal HP Deprivation Index Scores. The Relative HP Deprivation Scores are derived by subtracting the underlying trend from the absolute HP Deprivation Scores and rescaling them so that they have a mean of zero and a standard deviation of ten at each census wave. Thus, for the development of a social inclusion plan, the targeting of resources towards the most disadvantaged areas, or the development of a formal resource allocation system, the appropriate deprivation measure to use is the 2016 Relative Index Score. This shows the position of any given SA *relative* to *all other SAs* and is based on the latest available data from the 2016 Census of Population.

Table 1: Distribution of Absolute and Relative Pobal HP Deprivation Scores, 2006 to 2016

HP Index	Number of SAs	Minimum	Maximum	Mean	Std. Deviation
2006 Absolute Index score	18,488	-41.5	38.3	0.0	10.0
2011 Absolute Index score	18,488	-35.6	30.5	-6.6	9.5
2016 Absolute Index score	18,488	-40.9	35.5	-4.1	9.9
2006 Relative Index score	18,488	-41.5	38.3	0.0	10.0
2011 Relative Index score	18,488	-30.8	40.0	0.0	10.0
2016 Relative Index score	18,488	-39.9	40.8	0.0	10.0

Figure 3: Distribution of Absolute Index Scores, 2006 to 2016

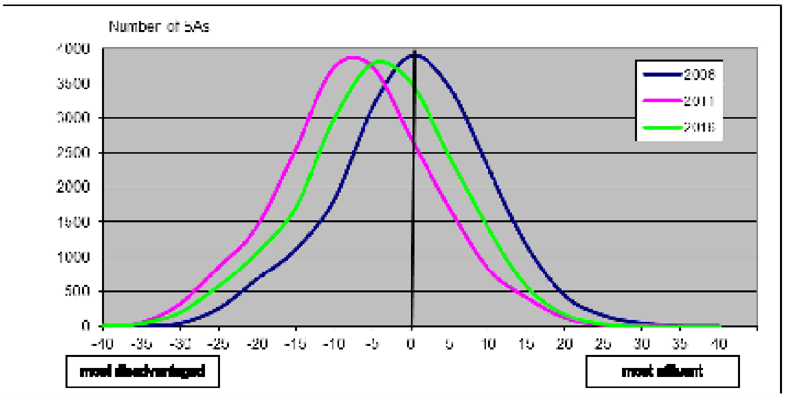


Figure 3 is based on the same data as summarised in Table 1, but shows the distribution of SA scores for each Census wave. Each line shows the number of SAs at each point of the distribution of Absolute HP Deprivation Scores[1]. The 2006 distribution is shown by the dark blue line. The recession in 2008 resulted in a significant decline in the Absolute HP Index Scores, as shown also in Table 1. In Figure 3, this effect is visible from the left-ward shift in the distribution of Absolute HP Index Scores between 2006 (dark blue) and 2011 (pink).

Between 2011 (pink) and 2016 (green), by contrast, the Irish economy partially recovered. This is reflected in the increase of the mean Absolute HP Deprivation scores from -6.6 in 2011 to -4.2 in 2016 (see Table 1) and in the right-ward shift of the distribution of SA-level Absolute HP Index Scores in Figure 3.

This demonstrates some of the key strengths of the Pobal HP Deprivation Index. Unlike other deprivation indices, which can only provide a ranking of areas, the Pobal HP Deprivation Index uses Confirmatory Factor Analysis (CFA) in its construction, which provides for a stable measurement scale across successive census waves. This is why we can make direct comparisons using both Absolute and Relative HP Deprivation Index scores.

In summary, the HP Deprivation scores can be used in different ways: (i) the Relative HP Deprivation Score provides a measurement of the affluence/deprivation of a given area relative to the national mean at a specific point in time, (ii) comparison of Absolute HP Deprivation scores from different census waves provides us with a measure of how much an area has improved or deteriorated in absolute terms, (iii) changes in the mean of the Absolute HP Deprivation scores indicates the underlying trend of how affluence/deprivation has changed over time, (iv) by comparing Relative HP Deprivation Index scores for a particular area at two different points in time, we can assess whether it has moved up or down in its position relative to the rest of the country.

Why are the Pobal HP Deprivation Index scores not expressed as decile rankings?

Decile rankings divide all geographical areas into ten equally-sized categories. This is frequently used for mapping purposes, or when comparing scores from indices that do not have a common measurement scale across successive waves of data. However, it is important to be aware that this use of decile rankings

[1] The lines are constructed as a smoothed curve over a bar chart using intervals of one half standard deviation, or 5 points on the HP index scale.

3 Reading the Tables, Graphs and Maps

The Excel data files for the 2016 Pobal HP Deprivation Index for Small Areas (SA) include the following:

A. Two composite index scores (the Absolute HP Index Score and the Relative HP Index Score)
B. Ten key socio-economic indicators used to construct the index and which are critical for interpreting the scores
C. Three additional indicators related to housing tenure which are not used in the HP Deprivation Index construction, but are nevertheless highly informative

The tables presented in the next section show the aggregate scores for the 34 Local Authority Areas (NUTS4), the 8 Regional Authorities (NUTS3), the two NUTS2 Regions (Southern & Eastern Region and Border, Midlands and Western Region) and Ireland as a whole (NUTS1). These provide important reference values when interpreting the relative affluence or deprivation of any specific area.

Excel data files containing data for NUTS5 (EDs) can be freely downloaded from the website www.trutzhaase.eu.

The full SA-level data are only available by signing a licence agreement, but the scores can nevertheless be visualised using the interactive mapping tools provided by Pobal Maps (https://maps.pobal.ie/). All supporting material concerning the Pobal HP Deprivation Index can also be downloaded from www.trutzhaase.eu .

4 Reference Tables

The first three index scores in Table 3 show the absolute level of affluence and deprivation for 2006, 2011 and 2016. The weighted mean index score fell dramatically during this period, from 0.4 in 2006 to -6.4 in 2011. The partial recovery of the economy resulted in an increase in the weighted mean HP deprivation index score to -3.6 in 2016. It is thus possible to say that the recovery in recent years has made up about two-fifths of the decline experienced during the recession.

One of the most interesting questions with regard to the most recent census data is how the economic downturn has affected different parts of the country. One important insight from a previously-published comparison of ED-level maps of Absolute Index Scores for 1991-2006 relates to the spatial distribution of growing affluence, and the overriding importance of Ireland's urban centres: *"The most affluent areas of the country are distributed in concentric rings around the main population centres, mainly demarcating the urban commuter belts. The measures show how rapidly these rings of affluence expanded during the 1990s, as large-scale private housing development took place in the outer urban periphery, generating high concentrations of relatively affluent young couples"* (Haase and Pratschke, 2008).

Looking at the maps in the accompanying Powerpoint presentations and in Table 3 below, we can see that urban areas have remained central to economic growth and development. In fact, the rings of affluence mentioned above, particularly around the Greater Dublin Region, were less affected by the crisis than more disadvantaged areas of the city and more isolated rural areas. Whilst Ireland as a whole saw a decline in mean Absolute HP Index Score by 6.6 points, Dublin City declined by just 5.8 points (Cork City by 4.1 points, Limerick City by 6.1, Galway City by 4.9 and Waterford City by 5.8). The counties coinciding with the most distant urban commuter belts – Kildare, Meath, Wexford, Roscommon, Cavan, Laois and Offaly – experienced the most significant decline, according to their Relative HP Index Scores. The housing estates that were developed in these counties towards the end of the boom experienced the greatest difficulties in terms of sustainability, due to inflated property values and the relative lack of local services and opportunities.

Table 3: Absolute and Relative HP Deprivation Index Scores*

Local Authority Area	Absolute HP Index Score 2006	Absolute HP Index Score 2011	Absolute HP Index Score 2016	Relative HP Index Score 2006	Relative HP Index Score 2011	Relative HP Index Score 2016	Relative HP Index Score 2006-16
Dublin City	-1.2	-4.5	-1.5	-1.2	2.2	3.1	4.3
South County Dublin	-.3	-4.7	-4.0	-.3	-.1	.9	.8
Dublin Fingal	4.8	-1.7	1.0	4.8	5.1	5.8	.7
Dun Laoghaire/Rathdown	7.8	3.6	6.1	7.8	10.6	10.8	2.2
Kildare	3.2	-4.4	-1.1	3.2	2.6	3.2	-.1
Meath	2.6	-5.7	-1.3	2.6	.9	1.8	-.8
Wicklow	1.1	-5.5	-1.7	1.1	1.0	1.4	.3
Carlow	-2.9	-8.8	-7.9	-2.9	-3.4	-3.7	-.7
Kilkenny	-.5	-7.5	-4.4	-.5	-1.0	-.3	.3
Wexford	-4.0	-11.4	-8.8	-4.0	-5.1	-4.8	-.8
Tipperary SR	-3.8	-8.9	-8.8	-3.8	-3.4	-4.4	-.7
Waterford City	-5.8	-10.7	-9.2	-5.8	-4.4	-4.8	1.0
County Waterford	-1.3	-7.6	-4.6	-1.3	-1.1	-.6	.7
Cork City	-4.2	-8.5	-5.1	-4.2	-1.9	-.4	3.7
County Cork	2.5	-3.8	-.7	2.5	2.9	3.4	.8
Kerry	-2.8	-8.8	-3.4	-2.8	-1.8	-1.8	1.0
Clare	-.2	-6.7	-4.3	-.2	-.1	-.2	.0
Limerick City	-7.4	-12.8	-10.6	-7.4	-6.8	-6.8	1.1
County Limerick	1.5	-5.7	-1.2	1.5	.5	.8	-.7
Tipperary NR	-1.8	-8.5	-6.1	-1.8	-2.0	-2.1	-.3
Galway City	2.7	-1.7	.0	2.7	5.2	4.8	2.1
County Galway	-.3	-6.6	-3.5	-.3	.0	.4	.3
Mayo	-4.1	-8.8	-7.7	-4.1	-3.1	-3.8	.3
Roscommon	-1.2	-8.7	-5.3	-1.2	-2.1	-2.4	-1.2
Louth	-3.8	-8.8	-7.2	-3.8	-3.3	-3.0	.5
Leitrim	-2.1	-8.8	-7.1	-2.1	-2.8	-3.2	-1.1
Sligo	-.7	-6.7	-5.6	-.7	-.1	-1.6	-.8
Cavan	-2.9	-10.9	-8.0	-2.9	-3.9	-3.8	-1.0
Donegal	-7.1	-12.5	-10.3	-7.1	-6.8	-6.4	.7
Monaghan	-3.1	-10.5	-7.3	-3.1	-4.0	-3.2	-.1
Laois	-1.4	-8.8	-5.7	-1.4	-2.8	-2.5	-1.2
Longford	-5.0	-11.4	-10.2	-5.0	-6.1	-6.0	-1.0
Offaly	-3.3	-11.0	-8.7	-3.3	-4.6	-4.6	-1.3
Westmeath	-1.4	-8.5	-6.2	-1.4	-1.9	-2.1	-.7
Region							
Dublin	1.8	-3.0	-.2	1.8	3.7	4.1	2.3
Mid East	2.5	-5.1	-1.8	2.5	1.5	2.3	-.2
South East	-3.0	-8.6	-7.3	-3.0	-3.2	-3.2	-.2
South West	.2	-5.7	-1.3	.2	1.0	1.7	1.5
Mid West	-1.1	-7.8	-5.2	-1.1	-1.1	-1.1	.0
West	-1.0	-7.0	-4.5	-1.0	-.3	-.4	.6
Border	-4.1	-10.4	-8.1	-4.1	-4.0	-3.9	.1
Midlands	-2.4	-9.8	-7.8	-2.4	-3.1	-3.4	-1.0
NUTS II Region							
S2	.4	-5.4	-2.8	.4	1.2	1.7	1.3
BMW	-2.6	-9.0	-6.7	-2.6	-2.5	-2.6	.0
Ireland	-.4	-6.4	-3.6	-.4	.2	.5	.9

* *Note: All scores shown in this and subsequent tables are population-weighted aggregates of the SA-level HP index.*

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Table 4: Total Population and 5-Year Population Change

Local Authority Area	Population 2002	Population 2006	Population 2011	Population 2016	Population Change 2006	Population Change 2011	Population Change 2016
Dublin City	495,808	506,286	527,612	554,554	2.0	4.2	5.1
South County Dublin	238,835	246,935	265,205	278,767	2.9	7.4	5.1
Dublin Fingal	196,556	239,855	273,991	295,759	22.0	14.2	8.0
Dun Laoghaire/Rathdown	190,237	193,643	206,261	218,258	1.8	6.5	5.8
Kildare	179,081	186,335	210,312	222,504	7.7	12.9	5.8
Meath	148,028	162,831	184,135	194,944	11.3	13.1	5.9
Wicklow	118,708	126,194	136,640	142,425	6.3	8.3	4.2
Carlow	47,945	50,349	54,612	56,881	5.0	8.5	4.2
Kilkenny	80,280	87,558	95,419	99,232	9.1	9.0	4.0
Wexford	121,552	131,749	145,320	149,722	8.4	10.3	3.0
Tipperary SR	80,849	83,221	88,432	88,271	2.9	6.3	-.2
Waterford City	44,018	45,748	46,732	48,216	3.9	2.2	3.1
County Waterford	59,338	62,213	67,063	67,960	4.9	7.8	1.8
Cork City	120,088	119,418	119,230	125,657	-.6	-.2	5.4
County Cork	340,317	361,877	399,802	417,211	6.3	10.5	4.4
Kerry	135,579	139,835	145,502	147,707	3.1	4.1	1.5
Clare	106,467	110,950	117,196	118,817	4.2	5.6	1.4
Limerick City	59,259	59,790	57,106	58,259	.9	-4.5	2.0
County Limerick	118,579	124,265	134,703	136,640	4.8	8.4	1.4
Tipperary NR	66,174	66,023	70,322	71,282	4.3	6.5	1.4
Galway City	65,722	72,414	75,529	78,668	9.3	4.3	4.2
County Galway	143,049	159,256	175,124	179,390	8.2	10.0	2.4
Mayo	119,744	123,839	130,638	130,507	3.4	5.5	-.1
Roscommon	55,300	58,768	64,065	64,544	6.1	9.0	.7
Louth	106,048	111,267	122,897	128,884	4.9	10.5	4.9
Leitrim	26,300	28,950	31,798	32,044	10.1	9.8	.8
Sligo	58,000	60,894	65,393	65,535	5.0	7.4	.2
Cavan	56,516	64,003	73,183	76,176	8.6	14.3	4.1
Donegal	141,213	147,264	161,137	159,192	4.2	9.4	-1.2
Monaghan	54,267	55,997	60,483	61,386	3.2	8.0	1.5
Laois	60,553	67,059	80,559	84,697	10.7	20.1	5.1
Longford	32,097	34,391	39,000	40,873	7.1	13.4	4.8
Offaly	63,349	70,868	76,687	77,961	8.3	8.2	1.7
Westmeath	71,081	79,346	86,164	88,770	8.7	8.6	3.0
Region							
Dublin	1,122,292	1,186,656	1,273,069	1,347,359	5.6	7.3	5.8
Mid East	437,658	475,952	531,087	559,873	8.6	11.7	5.4
South East	459,970	480,686	497,578	510,868	5.3	8.6	2.6
South West	596,152	621,130	664,534	690,575	4.2	7.0	3.9
Mid West	347,474	361,025	379,327	384,998	3.9	5.1	1.5
West	380,002	414,277	445,356	453,109	5.7	7.5	1.7
Border	446,421	468,375	514,081	523,217	5.1	8.8	1.8
Midlands	234,220	251,664	282,410	292,301	7.4	12.2	3.5
NUTS II Region							
SE	2,941,785	3,105,021	3,345,595	3,493,234	5.5	7.7	4.4
BMW	1,071,863	1,134,316	1,242,037	1,268,627	5.8	8.8	2.1
Ireland	4,013,448	4,239,848	4,588,252	4,761,865	5.6	8.2	3.8

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Table 5: Age Dependancy and Lone Parent Rates

Local Authority Area	Age Dependency Rate 2006 %	Age Dependency Rate 2011 %	Age Dependency Rate 2016 %	Lone Parent Rate 2006 %	Lone Parent Rate 2011 %	Lone Parent Rate 2016 %
Dublin City	27.7	27.8	28.1	31.5	30.4	27.6
South County Dublin	28.8	31.8	34.1	25.9	26.1	23.4
Dublin Fingal	28.1	31.5	33.7	21.6	21.1	19.6
Dun Laoghaire/Rathdown	31.6	32.7	34.3	17.5	16.9	14.8
Kildare	29.9	32.4	34.0	18.7	18.8	16.9
Meath	31.4	34.1	35.7	14.5	15.9	15.3
Wicklow	31.4	33.8	35.7	20.7	20.7	18.8
Carlow	31.5	33.6	35.1	21.1	20.6	20.3
Kilkenny	31.9	34.5	36.1	16.7	17.5	17.6
Wexford	33.8	33.4	36.7	21.2	22.7	22.2
Tipperary SR	32.9	34.7	36.3	21.8	22.5	22.8
Waterford City	31.3	32.8	34.2	31.6	31.8	31.4
County Waterford	34.2	35.8	37.4	15.9	18.1	16.8
Cork City	29.3	28.7	30.0	28.6	30.4	27.3
County Cork	33.3	34.1	35.8	18.0	16.8	13.5
Kerry	33.3	34.6	36.4	18.8	18.6	18.7
Clare	33.3	34.6	36.4	17.0	17.2	17.6
Limerick City	29.8	31.1	32.2	36.7	38.8	33.8
County Limerick	30.9	33.1	35.3	15.7	16.5	15.2
Tipperary NR	34.1	35.4	37.8	17.1	18.8	17.3
Galway City	23.9	15.9	29.1	28.0	24.7	22.3
County Galway	34.1	35.2	37.2	19.5	14.9	14.4
Mayo	34.3	33.8	37.8	15.6	17.7	16.6
Roscommon	36.2	33.8	37.8	14.0	18.2	18.8
Louth	33.3	34.3	35.9	22.6	23.7	22.7
Leitrim	34.9	36.4	38.5	15.5	15.7	15.4
Sligo	33.1	33.9	36.5	18.4	19.7	19.9
Cavan	34.6	33.7	36.8	14.7	16.9	13.6
Donegal	33.2	36.3	37.7	21.0	22.8	20.8
Monaghan	33.2	34.4	36.7	15.9	17.1	17.1
Laois	33.2	34.6	38.9	18.0	17.9	18.1
Longford	34.2	33.7	37.6	20.8	21.4	20.4
Offaly	33.5	35.0	36.3	18.4	18.8	19.2
Westmeath	33.9	33.9	35.1	18.6	18.5	16.8
Region						
Dublin	28.7	30.2	31.6	26.1	25.3	22.8
Mid East	30.8	32.4	35.0	17.7	17.8	16.3
South East	33.2	34.7	36.2	20.9	21.7	21.6
South West	31.8	33.4	34.8	19.1	18.4	16.4
Mid West	32.0	32.7	35.6	19.7	20.0	19.5
West	31.7	33.9	35.9	16.6	17.4	17.0
Border	34.0	33.2	36.8	19.1	20.4	19.7
Midlands	33.3	34.7	36.0	18.5	18.1	16.6
NUTS II Region						
SE	30.7	32.4	33.9	21.9	21.8	20.4
BMW	33.4	34.6	35.9	18.1	19.0	19.6
Ireland	31.4	33.0	34.5	20.9	21.0	18.8

Table 6: Percentage With Primary Education only and with a Third Level Education

Local Authority Area	Low Education 2006 %	Low Education 2011 %	Low Education 2016 %	Third Level Education 2006 %	Third Level Education 2011 %	Third Level Education 2016 %
Dublin City	21.8	18.1	14.3	35.8	37.7	44.3
South County Dublin	18.3	14.8	11.4	30.8	33.4	34.8
Dublin Fingal	10.8	9.2	8.0	39.5	37.8	42.7
Dun Laoghaire/Rathdown	9.7	8.1	6.4	50.8	51.6	57.4
Kildare	14.0	11.9	10.1	33.4	33.2	36.6
Meath	15.4	13.1	11.3	30.4	29.2	34.1
Wicklow	18.2	14.0	11.6	32.9	31.6	37.1
Carlow	19.7	16.9	14.4	24.5	24.5	29.5
Kilkenny	18.2	14.8	12.7	25.5	27.1	32.8
Wexford	22.8	18.8	18.8	21.8	21.7	28.7
Tipperary SR	20.0	16.9	14.8	21.9	22.3	28.8
Waterford City	19.3	16.5	14.6	26.0	26.1	29.8
County Waterford	18.1	15.4	12.7	27.1	27.4	32.5
Cork City	20.2	17.4	14.4	28.7	30.1	36.6
County Cork	13.4	13.4	10.8	31.9	31.7	36.8
Kerry	20.7	17.1	14.2	26.8	26.4	31.8
Clare	17.3	14.4	11.8	29.8	28.7	34.8
Limerick City	21.8	19.7	17.8	24.2	25.1	27.7
County Limerick	16.8	14.5	12.3	30.9	30.1	34.8
Tipperary NR	18.9	15.3	13.3	24.4	24.4	29.8
Galway City	11.1	9.9	8.6	44.7	44.7	48.6
County Galway	21.9	17.8	14.6	28.4	30.2	35.2
Mayo	24.8	20.8	17.1	28.1	24.3	28.9
Roscommon	21.7	17.8	15.1	28.4	24.0	28.8
Louth	21.3	18.3	15.4	28.1	23.7	30.9
Leitrim	22.5	19.2	15.5	25.6	25.7	26.9
Sligo	20.1	16.5	14.1	29.3	30.1	34.4
Cavan	23.4	20.3	17.4	23.4	22.4	26.1
Donegal	28.3	23.7	21.8	22.9	23.6	28.9
Monaghan	25.0	21.1	17.8	21.5	21.7	26.5
Laois	20.3	18.1	18.8	28.7	24.8	28.9
Longford	24.1	20.2	17.8	22.1	22.2	26.8
Offaly	21.9	18.6	16.1	21.9	21.6	25.5
Westmeath	19.5	16.4	18.9	25.9	27.0	31.8
Region						
Dublin	16.5	13.8	11.3	37.9	38.2	44.1
Mid East	15.1	12.9	10.9	32.3	31.5	36.6
South East	20.0	16.6	14.4	24.1	24.3	28.6
South West	17.6	14.3	11.9	30.1	30.3	33.9
Mid West	18.2	15.8	13.1	28.1	27.9	32.6
West	20.8	17.3	14.4	29.0	30.1	35.1
Border	24.7	21.0	17.7	24.8	24.6	28.2
Midlands	21.8	17.4	15.0	24.0	24.2	28.9
NUTS II Region						
SE	17.2	14.4	12.0	32.3	32.4	37.7
BMW	22.5	18.9	15.9	26.1	26.6	31.1
Ireland	18.6	15.6	13.0	30.6	30.6	35.9

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Table 7: Percentage of Population in Professional and Semi/Unskilled Classes

Local Authority Area	Professional Classes 2006 %	Professional Classes 2011 %	Professional Classes 2016 %	Semi/Unskilled Classes 2006 %	Semi/Unskilled Classes 2011 %	Semi/Unskilled Classes 2016 %
Dublin City	30.4	33.9	35.1	21.1	20.1	17.7
South County Dublin	32.6	34.0	36.7	17.8	18.4	16.8
Dublin Fingal	38.2	40.4	41.8	14.1	14.2	14.8
Dun Laoghaire/Rathdown	51.6	54.3	56.0	8.9	8.3	7.5
Kildare	35.5	37.9	40.0	17.8	16.1	15.9
Meath	35.3	37.2	38.1	17.0	16.2	16.5
Wicklow	36.7	38.1	40.4	17.4	16.3	16.3
Carlow	28.3	29.4	30.3	22.5	21.0	21.8
Kilkenny	34.2	34.8	37.2	18.7	18.0	17.9
Wexford	28.8	30.0	30.9	22.1	21.8	21.5
Tipperary SR	28.7	28.9	30.1	23.7	23.9	22.7
Waterford City	24.4	26.8	27.1	25.2	24.2	24.5
County Waterford	34.3	35.3	37.1	20.4	20.3	18.8
Cork City	25.1	27.5	28.7	24.8	23.1	22.8
County Cork	36.3	37.1	39.1	17.7	17.3	16.8
Kerry	30.4	30.6	31.4	19.6	18.7	19.0
Clare	33.6	34.6	36.9	17.5	18.6	17.6
Limerick City	22.4	23.8	24.8	26.6	25.6	25.8
County Limerick	34.4	35.3	37.5	19.5	19.2	17.5
Tipperary NR	32.0	33.6	36.9	18.7	20.2	18.3
Galway City	31.6	34.7	35.6	21.1	20.0	20.8
County Galway	33.9	35.3	37.3	18.4	17.2	16.7
Mayo	28.6	30.2	31.7	21.1	20.7	20.6
Roscommon	32.5	32.1	33.1	18.1	17.3	16.6
Louth	28.1	31.1	32.1	22.8	20.4	20.8
Leitrim	30.2	31.7	33.4	19.0	17.9	17.7
Sligo	33.3	33.7	34.6	18.4	18.4	18.2
Cavan	26.3	28.2	29.4	20.7	20.6	20.9
Donegal	27.8	28.8	28.9	23.7	21.8	21.6
Monaghan	26.8	27.9	29.2	21.7	22.8	22.1
Laois	28.7	31.2	31.3	20.8	20.4	18.4
Longford	27.2	27.7	27.7	21.8	20.6	22.3
Offaly	27.9	28.7	29.9	22.4	21.5	21.5
Westmeath	31.1	32.6	33.6	18.1	18.3	18.6
Region						
Dublin	35.8	38.7	40.5	16.9	15.7	15.8
Mid East	35.8	37.9	39.5	17.4	16.2	16.2
South East	30.3	31.1	33.4	22.0	21.2	20.8
South West	32.6	34.0	36.6	19.8	18.7	18.8
Mid West	31.7	32.8	34.4	20.4	20.1	18.9
West	32.0	33.5	34.8	18.7	18.6	18.4
Border	29.0	29.8	31.1	21.9	20.7	20.5
Midlands	28.3	30.3	31.4	20.9	19.9	20.1
NUTS II Region						
S&E	33.6	35.9	37.5	18.7	17.6	17.1
BMW	30.2	31.3	32.5	20.8	19.8	20.0
Ireland	32.6	34.6	36.2	19.3	18.2	17.9

Table 3: Unemployment Rates

Local Authority Area	Male Unemployment 2006 %	Male Unemployment 2011 %	Male Unemployment 2016 %	Female Unemployment 2006 %	Female Unemployment 2011 %	Female Unemployment 2016 %
Dublin City	12.5	23.3	14.9	8.5	15.1	12.1
South County Dublin	8.8	21.8	14.8	9.1	18.2	12.8
Dublin Fingal	7.7	17.9	10.3	8.0	14.1	10.6
Dun Laoghaire/Rathdown	5.8	15.1	8.1	5.0	9.6	7.2
Kildare	6.6	20.6	11.9	7.1	15.3	11.2
Meath	6.3	21.1	11.8	7.4	14.6	11.4
Wicklow	6.8	22.8	13.6	7.5	15.0	11.5
Carlow	9.4	26.6	17.5	8.7	19.1	16.8
Kilkenny	6.4	21.4	14.1	7.0	14.8	11.8
Wexford	9.7	28.7	18.0	9.2	18.1	18.2
Tipperary SR	9.1	24.8	16.9	8.2	15.7	14.2
Waterford City	14.1	30.3	21.3	11.6	20.6	17.8
County Waterford	8.8	21.1	14.0	7.8	14.3	11.1
Cork City	12.8	26.9	17.5	10.6	17.6	13.7
County Cork	5.8	17.8	9.8	6.1	11.8	8.8
Kerry	9.2	21.8	13.8	8.2	14.8	11.3
Clare	7.8	21.1	13.6	7.8	15.0	11.8
Limerick City	16.7	33.1	23.6	13.3	24.6	20.3
County Limerick	6.8	20.7	12.3	7.0	14.3	11.2
Tipperary NR	7.8	22.0	14.3	7.8	15.3	12.7
Galway City	12.9	21.7	14.5	10.1	15.8	12.2
County Galway	6.3	21.6	13.1	7.4	15.8	10.4
Mayo	8.6	23.6	16.8	8.8	14.8	12.8
Roscommon	6.2	22.4	14.0	6.6	14.3	12.2
Louth	11.8	28.0	18.0	11.1	19.2	18.5
Leitrim	8.3	25.1	16.5	7.9	14.5	12.1
Sligo	9.0	21.7	15.1	5.9	13.1	12.2
Cavan	8.0	24.3	15.3	8.8	17.3	13.8
Donegal	14.7	31.7	20.3	11.0	20.4	18.8
Monaghan	8.6	24.4	13.6	7.4	15.6	12.4
Laois	6.8	28.1	18.7	8.4	18.8	18.8
Longford	10.5	27.9	20.3	12.9	20.7	19.8
Offaly	8.3	26.4	16.3	8.2	19.4	15.9
Westmeath	8.3	23.0	18.6	9.0	17.3	15.5
Region						
Dublin	9.8	20.5	12.6	8.4	14.2	11.1
Mid East	6.5	21.3	12.3	7.5	15.0	11.4
South East	9.6	26.2	18.6	8.8	18.6	14.2
South West	8.0	20.8	12.0	7.8	13.8	10.8
Mid West	8.9	23.2	14.8	8.5	16.3	12.9
West	9.1	22.6	14.4	8.2	14.5	11.5
Border	11.2	27.4	17.4	8.4	17.3	14.8
Midlands	8.2	26.8	18.6	8.4	18.2	16.8
NUTS II Region						
SE	8.8	21.8	13.3	8.1	14.8	11.6
BMW	9.8	25.3	16.3	9.0	15.6	13.8
Ireland	8.1	22.7	14.1	8.8	15.3	12.2

Table 9: Housing

Local Authority Area	LA Rented 2006 %	LA Rented 2011 %	LA Rented 2016 %	Privately Rented 2006 %	Privately Rented 2011 %	Privately Rented 2016 %
Dublin City	13.1	12.2	12.9	24.5	32.8	32.9
South County Dublin	10.7	11.2	11.8	10.5	17.8	18.1
Dublin Fingal	8.9	8.7	6.8	12.3	21.6	22.7
Dun Laoghaire/Rathdown	5.8	6.0	6.6	18.2	19.9	21.0
Kildare	5.6	5.5	6.2	11.6	17.5	18.0
Meath	4.5	4.6	6.6	7.8	13.6	16.0
Wicklow	8.9	9.1	9.6	9.8	14.7	14.9
Carlow	7.5	8.8	10.7	13.1	16.9	17.1
Kilkenny	6.9	6.8	8.3	9.8	14.9	14.9
Wexford	7.7	8.8	9.1	10.5	14.5	15.0
Tipperary SR	8.2	8.0	10.8	8.7	14.8	14.6
Waterford City	14.1	16.4	17.6	18.6	21.6	23.4
County Waterford	5.8	7.2	7.7	7.7	10.8	11.7
Cork City	16.3	16.3	17.6	20.9	27.4	28.5
County Cork	4.6	5.2	6.1	10.7	16.0	16.4
Kerry	6.7	7.4	7.8	11.5	15.9	15.7
Clare	4.8	5.4	6.2	10.4	14.5	15.3
Limerick City	10.4	12.5	15.1	18.6	25.9	25.6
County Limerick	4.2	4.7	8.8	11.6	18.8	17.1
Tipperary NR	6.6	7.3	8.5	9.3	13.3	13.9
Galway City	8.6	8.8	10.8	18.1	20.6	30.9
County Galway	3.6	4.1	4.3	9.5	13.3	14.1
Mayo	4.6	4.6	5.5	10.5	14.7	15.5
Roscommon	4.4	5.4	6.0	8.5	12.9	13.6
Louth	7.9	8.8	9.8	10.2	15.6	16.6
Leitrim	7.6	7.4	7.8	10.3	14.8	15.0
Sligo	7.7	8.0	9.4	12.8	17.6	17.3
Cavan	6.0	6.3	7.7	9.5	15.0	15.9
Donegal	7.4	8.2	6.8	9.3	13.9	13.6
Monaghan	5.2	6.8	7.4	8.4	13.0	14.6
Laois	6.9	7.7	9.1	8.3	13.8	15.1
Longford	11.2	13.1	13.4	11.8	16.9	18.0
Offaly	6.0	7.1	8.3	8.8	13.7	14.6
Westmeath	5.5	6.7	7.7	12.2	17.5	18.9
Region						
Dublin	8.9	8.8	10.1	17.3	23.2	25.7
Mid East	6.0	6.1	6.7	9.8	15.4	16.2
South East	7.8	8.8	10.0	10.5	14.8	15.6
South West	7.5	7.7	8.6	13.5	17.8	18.5
Mid West	6.6	6.8	7.6	12.3	16.9	17.1
West	4.9	5.4	6.0	14.2	16.2	16.7
Border	7.1	7.6	8.7	10.6	14.6	15.1
Midlands	6.6	6.9	9.1	10.2	15.4	16.6
NUTS II Region						
SE	8.1	8.2	8.0	15.7	18.8	20.6
BMW	6.2	7.6	7.8	11.8	16.0	16.8
Ireland	7.6	7.8	8.7	13.1	18.7	18.4

5 Key Features of the Pobal HP Deprivation Index

The Pobal HP Deprivation Index permits the longitudinal study of affluence and deprivation between 2006 and 2016, as well as allowing a precise analysis of relative scores at each census wave. The index was designed by Trutz Haase and Jonathan Pratschke and funded by Pobal Ltd. In this section, we highlight some of the key features of the Pobal HP Deprivation Index which set it apart from other deprivation indices.

- ☐ **no double-counting**

The techniques used to calculate the index scores avoid the double-counting that typically results when indicators are summed together.

- ☐ **indicator selection**

The choice of indicators for the Pobal HP Deprivation Index is based on the principle that at least three indicator variables should be specified for each dimension, and that additional indicators should be included only if they are consistent with the hypothesized model.

- ☐ **a range of statistical tests and alternative fit indices can be used to test model adequacy**

The dimensions identified in exploratory factor analyses can be unstable and even counter-intuitive. By contrast, in confirmatory factor analysis models, statistical tests and alternative fit indices provide a systematic way of assessing whether the theoretical model (i.e. our ideas about the key dimensions of deprivation and their relationship with a set of indicator variables) is consistent with the empirical evidence.

- ☐ **stable measurement scales across multiple waves**

When exploratory techniques are used, the factor structure varies with each new dataset, and cannot be fixed across multiple waves. This means that the scores from a series of Exploratory Factor Analyses cannot be compared across successive waves of census data. Because it relies on a confirmatory approach, the HP Index has a stable factor structure and measurement scale, and its scores can be compared over time and across different jurisdictions.

- ☐ **true distances from mean are maintained**

Deprivation indices based on exploratory techniques typically rely on a ranking of areas to compare results from one census wave to another. However, rankings contain much less information than scores, and typically over-emphasise the importance of small differences, particularly at the centre of the distribution. The HP Index, by contrast, maintains true comparability of actual deprivation scores from one census to another. It is the first deprivation index to achieve this goal at international level, and this is one of the most important advances pioneered by Haase and Pratschke in the construction of composite deprivation indices.

- ☐ **distinction between absolute and relative deprivation scores**

As the measurement scale of the HP Index is invariant across successive census waves, it is possible to derive both absolute and relative deprivation scores. Absolute scores are fixed to a particular reference point (e.g. the 2006 census) and reveal patterns of change over time. Relative deprivation scores are de-trended and focus on the relative distribution of affluence and deprivation at a single point in time.

normal distribution of scores from affluence to deprivation

Unlike other deprivation indices (including, in particular, those which attempt to estimate the number of poor people in a given area), the HP Index is approximately normally distributed, with scores ranging across the full spectrum from extreme affluence to extreme deprivation. This is of considerable importance when using the index to explore inequalities such as the "social gradient" in health outcomes, or the health needs of a population.

Close examination of the HP Index by the Central Statistics Office during early 2012 led the CSO to adopt this measure as the main stratification tool for the sampling design of all future CSO household surveys (QNHS, EU-SILC, the future wealth survey and future general household survey). In a recent study, conducted by Haase and Pratschke for the CSO, the aforementioned statistical properties of the index were shown to be a major asset when conducting aggregate-level analyses.

The new census geography of small areas

Since 2011, the Small Area Population Statistics (SAPS) are published at the level of Small Areas (SAs). SAs are standardised in size, 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 Electoral Divisions (EDs) – which could range in population from under 100 to over 82,000 – marks a major advance, particularly where a census-based deprivation index is used as a proxy for individual-level social position.

Consistent coverage over successive census

In 2011, the SAPS comprised 18,488 SAs. To maintain confidentiality, the CSO had to amalgamate some of these SAs in 2016, which leads to difficulties when looking at data across multiple census waves. The 2016 Pobal HP Deprivation Index is constructed using the 2011 Small Area definitions of the CSO, so as to maintain comparability and to avoid unnecessary changes in units. In this way, data relating to any one area – be it at the SA level or any subsequent spatial aggregation – can be compared across the three census waves from 2006 to 2016. The 2016 Pobal HP Deprivation Index is the only dataset in Ireland to have adopted the new Small Area census geography using the 2006, 2011 and 2016 census data in a consistent manner.

6 Questions and Answers

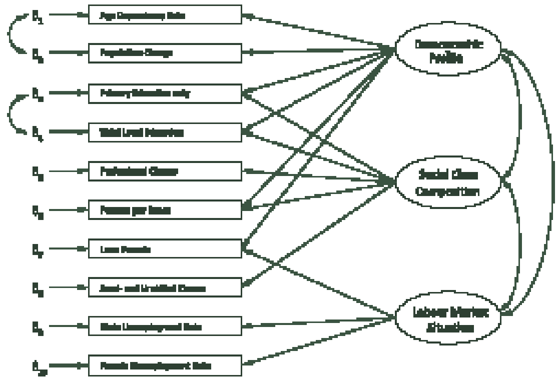
❑ Q: What concept of deprivation does the HP Derivation Index aspire to quantify?

The fundamental concept of deprivation that lies at the heart of the Pobal HP Deprivation Index is the concept of relative deprivation advanced by Coombes et al. (UK – Department of the Environment, 1995), namely that "The fundamental implication of the term deprivation is of an absence – of essential or desirable attributes, possessions and opportunities which are considered no more than the minimum by [that] society."

Whilst indicators relating to attributes and possessions are used in a wide number of deprivation indices, the novel aspect of this definition lies in the inclusion of opportunities, and hence opportunity deprivation, as a key aspect of deprivation. Opportunity deprivation lies at the heart of much of rural deprivation, which is of relevance to many areas in Ireland. In this respect, the Pobal HP Deprivation Index has a different conceptual basis to other indices and is able to provide a robust measure of relative affluence and deprivation across both urban and rural areas.

❑ Q: How is the HP Deprivation Index constructed?

The figure below shows a graphical representation of how the concepts of Demographic Growth, Social Class Composition and Labour Market Situation are measured by ten key socio-economic indicators from the Census of Population.



❑ Q: What about other deprivation-related indicators which are not included in the Pobal HP Deprivation Index?

A number of other indicators related to poverty and deprivation could potentially be used to measure deprivation, but are deliberately not included in the Pobal HP Deprivation Index for reasons which will be explained below. Such indicators could capture various aspects of the domains of health, wealth, housing, environment and crime, for example. One reason for this is the decision to rely exclusively on the census of population for indicators:

- Ireland is in a unique position in that it is the only European country that is committed to carry out a Census of Population every five years, and each new wave of data is quickly released. Policy makers can therefore feel assured that by using the Pobal HP Deprivation Index they are basing their decision on very up-to-date information. In jurisdictions where the Census is carried out every ten years (such as the UK and Northern Ireland), doubts about the accuracy and timeliness of information reduce reliance on the census when making policy-relevant decisions.

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- Using Census data, and census data only, ensures the development of robust and stable concepts which maintain their validity and comparability over time and space. This is evidenced by the development of an All-Island HP Deprivation Index, using identical census variables for both jurisdictions.

Data Requirements:

A crucial element of the Pobal HP Deprivation Index is that it is a truly multidimensional measure constructed at the level of census Small Areas (SAs). This means that all of the information used in its construction must be available at the Small Area level. By contrast, the Northern Ireland Multiple Deprivation Measures (NIMDM) are not multidimensional at this level, as the Small Area component is centred on income measures, with other dimensions being incorporated at higher levels of spatial aggregation only.

Constructing a truly multidimensional deprivation index at the level of Small Areas requires very large datasets like the Census. By definition, this excludes indicators derived from survey data, as these would not be available for each of the 18,488 small areas in the country. Although it is, in theory, possible to draw on large administrative databases when developing indicators for Small Areas, this raises a number of difficulties regarding the stability of definitions and estimates, uniformity of treatment and the accuracy of data.

Health:

Health indicators are deliberately not included in the Pobal HP Deprivation Index because deprivation indices are frequently used to predict/explain health and health-related outcomes. The inclusion of health-related indicators (such as those provided by the census) in the construction of the Pobal HP Deprivation Index itself would create a circularity in relation to one of its principle applications.

Income and Wealth:

Data on income and wealth could potentially be accessed from the Revenue Commissioners, although there would be major challenges regarding data protection.

Income data also fluctuate considerably over time, across the life cycle and in accordance with family composition, which makes it more difficult to obtain stable and interpretable deprivation scores. Several studies point to the superior performance of a multi-dimensional measurement of income and wealth – preferably using Confirmatory Factor Analysis – rather than relying on a direct measurement of income or wealth (see e.g. Tomlinson, Walker, Williams, 2008). Research on health and well-being in the US, where income data are routinely available, increasingly relies on composite indicators of deprivation, as these provide more powerful insights into socio-economic influences.

Housing:

Housing data could potentially be derived from the Census, or from very large administrative datasets such as the CSO's Residential Property Price Index (RPPI) or commercial datasets. However, the RPPI uses the Pobal HP Deprivation Index as a key element in its construction, which would, once again, give rise to circularity.

Secondly, the very meaning of housing indicators can change over time and space. Many questions have been posed recently with regard to the inclusion of housing indicators within the Pobal HP Deprivation Index, with a view to understanding the impact of the 2008 recession. This includes problems of negative equity, inflated house prices and the affordability of rental accommodation. However important these issues may be, they vary quite rapidly over time, and it would be impossible to ensure the continuing validity of any related indicators over coming years and decades.

High levels of deprivation are generally observed in areas with high levels of local authority housing, which can be demonstrated by comparing the distribution of social housing with the Pobal HP Deprivation Index scores. It is for this reason that we typically supply information from the Census on the percentage of Local Authority rented accommodation alongside the Pobal HP Deprivation Index, and this indicator is also included within Pobal Maps.

At the same time, the inclusion of a measure of social housing within the Pobal HP Deprivation Index itself would give rise to a number of risks, and would again reduce the range of potential applications of the index itself. This is because the provision of social housing represents a type of benefit or social good. If this variable were included in the index, the level of deprivation in certain areas would appear to decline if the supply of social housing were reduced. This would be a contradictory and counter-intuitive result, as housing needs would actually increase in this case.

For this reason, the authors have argued strongly against the use of benefit data and housing data in the construction of deprivation indices and are critical of their inclusion in the Northern Ireland Multiple Deprivation Measures (NIMDM) and the UK Indices of Multiple Deprivation (IMD).

Environment

A number of environmental indicators could potentially be considered as indicators of deprivation. For example, there has been discussion about whether an urban-rural classification should be incorporated into deprivation indices (for a detailed discussion of this question, see Haase & Walsh, 2007). The authors have decided against this, as they believe that the way in which deprivation interacts with functional space and population density should be studied over time using sensitive multi-dimensional measures that capture specific types of deprivation.

In many applications, it may nevertheless be useful to combine the Pobal HP Deprivation Index with the CSO classification of area types. A good example for this kind of approach is the LEADER Resource Allocation Model, which places an additional weighting on more rural areas. Analogously, the Resource Allocation Model for Drugs and Alcohol Task Forces assigns an additional weighting to more urban locations. By maintaining the distinction between deprivation and the urban-rural spectrum, these kinds of decisions can be made in a context-sensitive way.

Another important aspect of the environmental context relates to transport. The National Transport Authority already uses the Pobal HP Deprivation Index to evaluate alternative transport routes. Inclusion of transport data within the index would lead, once again, to confounding and circularity. This is another example of how conceptual clarity is a virtue when designing deprivation indices, which are applied and used in many different ways and contexts, many of which cannot be determined in advance.

Another interesting aspect of the environmental context relates to the quality of the local area, including potential hazards such as noise, water and air pollution and access to amenities and services. As in the case of health, housing and transport, the authors believe that the association between deprivation and the local environment should be studied empirically, rather than incorporating this within the definition of deprivation itself.

Crime:

Crime data have been used in deprivation indices in other countries, but we do not believe that their inclusion would be beneficial to the Pobal HP Deprivation Index. One reason for this is the lack of consistent data and persisting doubts about the validity and stability of Small Area crime-related indicators over time and space. Policing is sensitive to political perceptions, operational decisions, public debate and local initiatives, which leads to systematic variations in how (and which) crimes are detected at the local level. In addition, it could be argued (as before) that one of the useful aspects of measuring deprivation at local level is that you can then explore how crime rates and the experience of crime and victimisation vary systematically across different kinds of neighbourhoods.

- **Q: How can one demonstrate the validity of the Pobal HP Deprivation Index?**

  A: The validity and usefulness of the Pobal HP Deprivation Index ultimately lies in its ability to predict and explain the socio-economic differentials observed in relation to health, well-being, education, financial position, housing, environment and crime. It is precisely because the Pobal HP Deprivation Index does not include indicators of these domains in its construction that one can use the Pobal HP Deprivation Index to empirically explain and predict outcomes. Its ability to do so with high explanatory power provides the ultimate demonstration of the validity of the Pobal HP Deprivation Index and underlines its primary role in shaping, guiding and monitoring public policies for an inclusive and sustainable society.