

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.

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 simple code evaluation (a single hospitalization with limited codes) or more complex (inpatient and out-patient encounters and many codes screened).⁵ Previous work, such as that of Barnett et al,³ identified 40 morbidities and were informed by a systematic review of multimorbidity measures⁶ – 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.⁵ From these they identified a panel of 30 chronic conditions that that could potentially facilitate the study and surveillance of multimorbidity.⁵ 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.

Declan Byrne¹
MB MSc FRCPI

Seán Cournane²
PhD

Richard Conway¹
MD MRCPI

Deirdre O’Riordan¹
MD FRCPI

Bernard Silke¹
MD DSc FRCPI

¹ Department of Internal Medicine, St James’s Hospital, Dublin 8, Ireland

² Medical Physics and Bioengineering Department, St. Vincent’s University Hospital, Dublin 4.

Correspondence

Declan Byrne
Department of Internal Medicine, St James’s Hospital, Dublin 8, Ireland
Email: debyrne@stjames.ie

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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-morbidity⁵ 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 m².¹⁶ 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 Townsend¹⁷ and Carstairs¹⁸ 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 incidences²¹ 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

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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 (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%)	

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 Index²⁶ 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 – 40.8% vs. 45.4%), Charlson Index (Grade

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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),

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

	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%)	

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 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	-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	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	29.82	35.71

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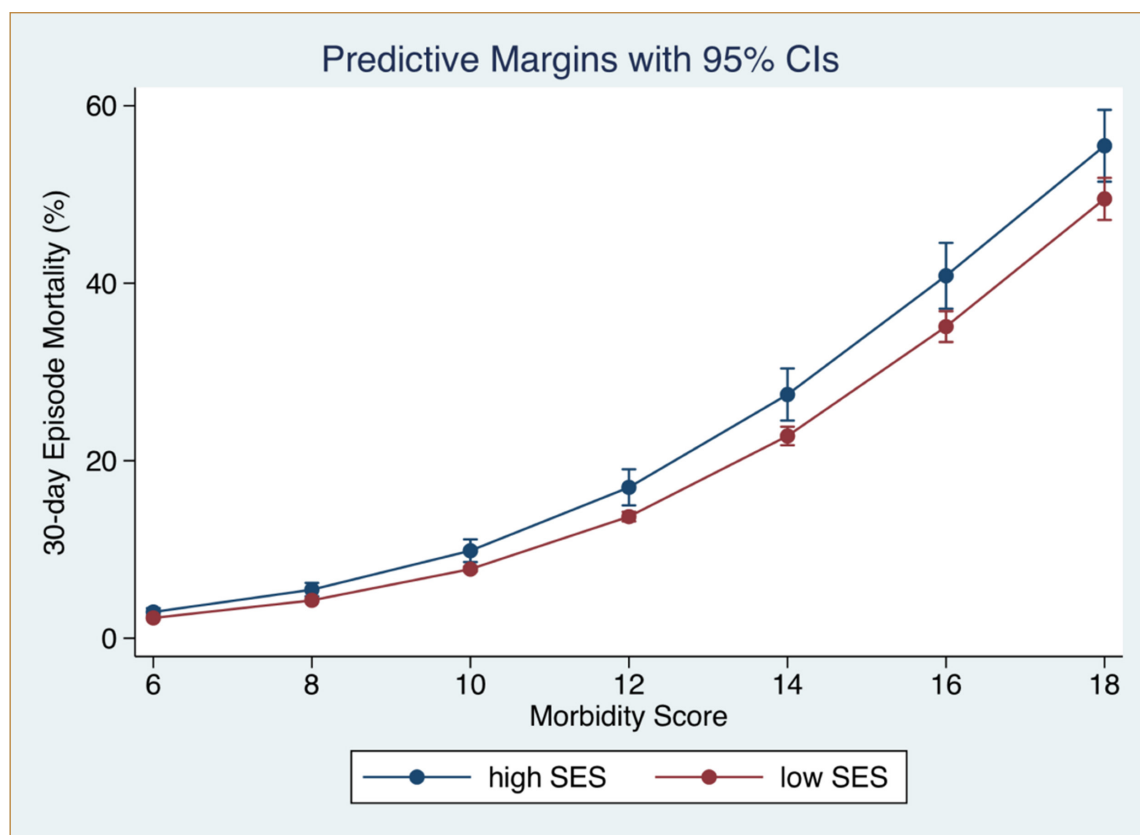


Figure 1. The 30-day hospital episode mortality outcome was non-linearly related to the Multi-Morbidity Score. The predicted probabilities were derived from the multiple variable logistic model; the effect is plotted based on the latter prediction. The older high SES group had a higher mortality predicted 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 consequence 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%

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for ED presentations where the social influences on emergency department visitations on two London hospitals have been examined.⁹

Interpretation

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 ($F = 24.5$, $P < 0.001$) 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 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.²⁸ 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.

Generalisability

This is a single centre retrospective study from a relatively deprived urban centre. This limits generalizability. For context, previous estimates of morbidity within populations was based on surveys such as Tonelli et al.⁵ 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-standardized 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%, 85.2% and 93.5% of these respective cohorts.

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. 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, gastrointestinal, diabetic and alcohol related are over expressed and are a manifestation of social or behavioural influences on life style.

Conclusion

The overall conclusion 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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