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Do ethnic and socio-economic inequalities in mortality vary by region in New Zealand? An application of hierarchical Bayesian modelling☆

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ABSTRACT

We hypothesised that ethnic and socio-economic inequality in mortality might vary by region in New Zealand. Linked 2001–2004 census-mortality data were stratified by region (District Health Boards or DHBs), sex, age and ethnic groups, and income quintiles. To accommodate data sparseness, and to achieve accurate estimates of DHB-specific mortality rates and rate ratios by ethnicity and income, we used hierarchical Bayesian methods. To aid presentation of results, we used posterior mortality rates from the models to calculate directly standardised rates and rate ratios, with credible intervals. Māori-European/Other mortality rate ratios were often similar across DHBs, but Waitemata and Canterbury DHBs (both predominantly urban areas with low Māori population) had significantly lower rate ratios. In contrast, Bay of Plenty and Waikato DHBs (heterogeneous by both ethnicity and socio-economic position) had significantly higher rate ratios. There was little variation in mortality inequalities by income across DHBs. Examining the underlying rates for ethnic and income groups separately, there were significant variations across DHBs, but these were often correlated such that the ethnic or income rate ratio was similar across DHBs. The application of hierarchical Bayesian allowed more definitive conclusions than routine empirical methods when comparing small populations such as social groups across regions. The range of hierarchical Bayesian estimates of Māori mortality and Māori:European rate ratios across regions was considerably narrower than empirical standardisation estimates.

Introduction

Cross-national and time comparisons of the magnitude of health inequalities are of etiological and policy interest. For example, varying inequalities in mortality by socio-economic position across countries may point to different diets, tobacco consumption and health care access by social group (Huisman et al., 2005; Mackenbach et al., 2003, 2008).

There is a large literature documenting inequalities in mortality by socio-economic position and race/ethnicity at the country-level, including for New Zealand (Blakely, Fawcett, Hunt, & Wilson, 2006; Blakely, Tobias, & Atkinson, 2008; Howden-Chapman & Wellington School of Medicine, 2000; Pearce, Davis, & Sporle, 2002; Tobias, Blakely, Matheson, Rasanathan, & Atkinson, in press).

There is also a literature describing mortality variations between regions within a single country, including New Zealand. For example, Pearce (2007) finds that variations in suicide between regions among men aged 14–44 increased during the period 1980–2001. Similarly, Pearce and Dorling (2006) and Pearce, Dorling, Wheeler, Barnett, and Rigby (2006) argue for increasing between-region variations in mortality and life expectancy between 1980 and 2001 using a relative index of inequality for age–sex standardised DHB mortality rates, and a slope index of inequality of male and female life expectancy, respectively.

Related approaches can be found in the small domain estimation literature (Congdon, 2003), where the focus is typically on combining information from small areas to make population

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inferences for the total domain. For example, Leyland, Langford, Rasbash, and Goldstein (2000) use spatial multi-level models to predict mortality caused by neoplasms and circulatory disease in 143 postcode sectors in the Greater Glasgow Health Board, Scotland. In another example, estimates of all-cancer mortality rates for white males in 798 US health service areas are provided by Nandram, Sedransk, and Pickle (1999) using a hierarchical Bayesian model.

However, there is little published work comparing social inequalities in mortality between regions of a given country. One exception is a comparison of empirical age adjusted social class mortality rates (1991–1993) by region within the UK (Uren, Fitzpatrick, Reid, & Goldblatt, 2001). Marked regional variations in mortality for men aged 20–64 within social classes were found across the UK, with rates generally higher in all social classes in Scotland, Northern Ireland and the north of England. Relative inequalities in male mortality between the highest and lowest social class were greatest in Northern Ireland and North East England (rate ratios of 5.2 and 4.3, respectively – actual ratios not given in source reference, but read from figures), and least in East, South East, South West and London regions of England (rate ratios approximately 2.2–2.4). Social class differences in adult self-reported health, based on empirical estimates of age-standardised rates of poor health, have also been found to vary by region in the UK (25–64 year olds, 2001 census data), but now London was one of the two highest relative inequality regions along with Scotland (Doran, Drever, & Whitehead, 2004). Both studies focus on regional variations in socio-economic inequalities, and use empirical methods to estimate standardised rates and rate ratios. This leaves open the question as to whether other dimensions of spatial inequality are important, and whether routine methods are adequate to investigate them.

A priori, there were grounds for expecting some regional variations in inequalities in mortality between Māori and European/Other. Colonisation of New Zealand began nearly 200 years ago. There were marked variations across New Zealand in the extent and timing of European–Māori contact (Belich, 1996; King, 2004). Further, there is a strong tribal (iwi) and regional basis to Māori culture – although many Māori recognise ancestral ties to several iwi, and/or often live outside the traditional boundaries of those iwi. There was some regional variation in European settler patterns with respect to country of origin, timing and main economic activity. More recent migration and immigration patterns are likely to significantly impact these historical processes. Regarding socio-economic inequalities in mortality, we did not expect much regional variation. Local governments have some autonomy of local amenities, but the main policy decisions are made centrally and implemented equivalently across New Zealand. For example, one social welfare and taxation system applies to all regions of New Zealand.

The linked census-mortality data in the New Zealand Census-Mortality Study (NZCMS: Blakely, Woodward, & Salmond, 2000; Fawcett, Atkinson, & Blakely, 2008) provide much useful information for quantifying such inequalities, and allow estimates of geographical variations in mortality and mortality inequalities using a more richly stratified dataset than have been possible in previous analyses. Even so, low person-years at risk and (particularly) deaths in some age, sex, ethnicity, income, and DHB strata are problematic for comparisons of mortality inequalities across regions. Hierarchical Bayesian models provide an approach to pooling information without forcing associations (e.g., between mortality rates and income) to be the same across strata. Thus, they give some protection against model misspecification while nevertheless permitting smoothing of crude rates. Hierarchical models have been shown to outperform classical regression in predictive accuracy (Gelman, 2006). Bayesian "shrinkage" estimators (discussed below) have good variance reduction properties, particularly when sample size is small (Best, Richardson, & Thomson, 2005; Greenland, 2008). The utility of hierarchical Bayesian regression techniques for the analysis of social variations in health outcomes appears not to have been widely recognised.

Why might regional variations in social inequalities in mortality be important? First, the determinants of health *inequalities* are not necessarily the same as the determinants of health (Blakely, 2008; CSDH, 2008; Krieger, 2008). For example, policy variations by region might widen or narrow health inequalities compared to other regions in the same country. Second, knowing about regional variations in health and health inequalities should assist with targeting future policies and programmes, as is already the case with knowledge of average health status by region. Third, some nations, including New Zealand, fund their public health systems at the regional level using socio-demographic predictors of public health and health care need, in addition to (or instead of) actual measures of health status. Therefore, it is of interest to regional health authorities whether regional variations in health (and inequalities in health) are accounted for by the variables used in such funding formulae. Finally, identification of regional variability may provide important clues about modifiable drivers of health inequalities.

Accordingly, the major goal of this paper is to determine whether mortality inequalities by ethnic and socio-economic position vary across regions in New Zealand. As the regional variable we use 21 District Health Boards (DHBs), described later. However, comparing mortality rate differences between social groups within regions of a small country like New Zealand leads to problems of sparse data. For example, the number of Māori (indigenous population of New Zealand) deaths in some DHBs is small. The problem of low stratum person-time at risk becomes worse if the analyses also have to account for sex, age and one (or more) measures of socio-economic position. Consequently, a secondary goal of this paper is to demonstrate the use of hierarchical Bayesian methods that accommodate issues of sparse data, and provide reliable estimates of uncertainties, better than the 'routine' quantitative methods used in previous studies. To emphasise this point, we also examine the difference that hierarchical Bayesian methods make to final results. Third, to understand social inequalities in mortality, it is important to first understand regional variations in group-specific mortality rates, and the contribution socio-demographic factors make to those variations. Thus, the three objectives of this paper, and subsidiary research questions, are:

1. Demonstrating social group differences in mortality across regions within New Zealand:
   a. Do mortality inequalities by ethnicity vary across regions?
   b. Do mortality inequalities by income vary across regions?
2. Demonstrating the utility of hierarchical Bayesian methods:
   a. Does the application of hierarchical Bayesian methods substantially alter findings, compared with simpler empirical methods?
3. Exploring mortality rate differences across regions:
   a. What is the variation in overall, Māori, European/Other, low- and high-income mortality rates by region?
   b. How much of the sex and age adjusted mortality rate differences by region is explained by ethnicity and income?

We are not aware of previous empirical research in New Zealand on our main objective of demonstrating social group inequalities in mortality by region. Additionally, whilst hierarchical Bayesian models have, in our view, clear theoretical advantages in the face of sparse data, they come at considerable cost in terms of complexity,

computing time and analytical expertise. Thus, we also compare hierarchical Bayesian results with routine direct standardisation results to determine what impact these more sophisticated analyses have on the final results. Regarding the third objective on variations in mortality rates between regions we present regional mortality rates adjusted for potential cofounders together with reliable estimates of uncertainty as a necessary first step, in our view, to interpreting social variations in mortality inequalities across regions.

Data and methods

Data

Linkage of 2001 census data to 2001–2004 mortality data in the NZCMS is described in detail elsewhere (Fawcett et al., 2008). Briefly, 81.5% of eligible mortality records (all ages) in the three years after the 2001 census were linked back to a 2001 census record (67,146 linked pairs). We estimated that over 97% of these linked pairs were correct linkages (Blakely & Salmond, 2002). Mortality records were less likely to be linked to a census record if any of the following conditions held: aged 25–34 years; an external cause of death; lived in the north of North Island; was of Pacific and Asian (and to lesser extent Māori) ethnicity compared to European/Other. Accordingly, we calculated inverse probability linkage weights to 'weight up' the linked pairs to be representative of all eligible mortality records. For example, if 20 out of 30 Māori male deaths aged 45–64 living in moderately deprived areas were linked, then the 20 linked pairs each received a weight of 1.5 (i.e., 30/20).

The variables used in the analysis were sex, age, ethnicity, household income, and DHB. We excluded Pacific and Asian people since they are concentrated in only a few DHBs, and the major focus of this study was the comparison between the two major ethnic groups Māori (anyone self-identifying as Māori on the census questionnaire) and European/Other (i.e., non-Māori non-Pacific non-Asian). District Health Boards were formed in 2000 with the statutory responsibility to deliver all publicly funded public health and health care services to their population (see Fig. 1 for a map of DHBs). Funding is received from central government via a population-based funding formula that uses sex, age, ethnicity and deprivation. Whilst DHBs are strictly health-related regions, they do have some consistency with smaller local government territorial authority boundaries. Household income was equivalised for the number of adults and children therein using a New Zealand-specific scale (Jensen, 1998). The total person-years available for analyses was 4.79 million (see Table 1), excluding 15% of respondents with missing household income.

The analyses were conducted on cross-classified counts for 240 strata within each DHB: sex [2] by age [12 five-year age groups] by ethnicity [2] by income [5 quintiles]. Sex and ethnicity were treated as dummy variables, with the reference group being males and European/Other, respectively. Age was centred on the 55–59-year age group, and scaled to units of 10 years. Household income quintiles were determined within each stratum of sex by five-year age group i.e., pooled across other strata including DHBs. Income was median-centred and scaled such that a one unit change in income was equivalent to a ten percentage point increase in income rank. Income quintile values, related in the model to the prior mean through a log-link function, were treated as a linear continuous variable. Previous research (Blakely, Kawachi, Atkinson, & Fawcett, 2004) has shown that treating income rank in this way is reasonable, and we considered the use of a simple initial prior model was preferable. As already noted, some protection against model misspecification is afforded by our hierarchical Bayesian approach. To allow for the non-linear increase in mortality with age, we fitted a linear spline function of age with knots at 45 and 65 years of age (Greenland, 1995).

Modelling – hierarchical Bayesian Poisson regression

The hierarchical Bayesian regression approach of Christiansen and Morris (1997) was applied by Young, Graham, and Blakely (2006) to Poisson count and rates using linked census-mortality data. In brief our method, based upon that of Young et al. (2006) was as follows. Assuming death is a Poisson process such that for DHB $j = 1,\ldots,21$ and stratum $i = 1,\ldots,240$ with deaths d_{ij}, mortality rate λ_{ij}, and person-years at risk P_{ij}, and using the notation $x \sim D[a,b]$ to represent a random variable x distributed as D with mean a and variance b, a three-level Poisson model was defined by:

$$d_{ij}|\lambda_{ij}, P_{ij} \sim \text{Poisson}\left[\lambda_{ij}P_{ij}, \lambda_{ij}, P_{ij}\right], \tag{1}$$

$$\lambda_{ij}|X_i, \beta_j, \varsigma \sim \text{gamma}\left[\mu_{ij}, \mu_{ij}/\varsigma^2\right], \tag{2}$$

$$\log\left(\mu_{ij}\right) = X_i\beta_j, \tag{3}$$

$$\beta_j, \varsigma \sim \pi. \tag{4}$$

The first level mortality rate parameter λ_{ij} had a gamma distribution at the second level with mean μ_{ij} and variance μ_{ij}/ζ^2, and the prior mean μ_{ij} had a structure that depended on covariates X_i and parameters β_j through a log-link function. Second-level parameters, β_j (the regression "hyper-parameters") and ζ (the mortality rate variance or "shape" hyper-parameter) were assigned independent prior distributions ("hyper-priors") at the third level of the hierarchy. The hyper-prior distributions π are described below.

Extending the Young et al. model to allow for variation by DHB, the regression parameter vector was partitioned as $\beta_j = (\beta_{1j}, \beta_2)$ to allow some of the components (the β_{1j}) to vary by DHB (i.e., intercept, ethnicity and income coefficients; see below). A standard approach was adopted for β_2, with uniform independent prior distributions for each component. The vector β_{1j} was assigned a multivariate normal prior distribution using the approach of Hossain, Graham, Gower, and Davis (2003) i.e., as a sequence of conditional normal distributions with uniform (0, 100) priors for each of the standard deviation parameters, and a uniform (−1, 1) prior for the correlation parameters.

The prior covariate structure influences the mean of the posterior rate, but the degree of influence depends on the overall support for the prior covariate structure in the data, as well as on how much local information is available. Given the structure of the model defined by equations (1) and (2), the conditional posterior distribution for the mortality rate is also gamma with mean

$$\text{E}\left[\lambda_{ij}|\mathbf{y}, \beta_j, \varsigma\right] = B_{ij}\mu_{ij} + (1 - B_{ij})y_{ij}, \tag{5}$$

where $y_{ij} = d_{ij}/P_{ij}$ is the observed mortality rate in the ith stratum of the jth DHB, $\mathbf{y} = (y_1, y_2,\ldots)$ and

$$B_{ij} = \varsigma/\left(\varsigma + \mu_{ij}P_{ij}\right). \tag{6}$$

Thus, the conditional posterior mean for λ_{ij} is a weighted average of the prior mean μ_{ij} and the observed mortality rate (y_{ij}). The B_{ij}, which lie between zero and one, are known as shrinkages because larger values shrink the conditional posterior mean mortality rates towards the prior mean. The gamma shape parameter ζ provides a measure of in the influence of the prior mean – large values of ζ correspond to small variation about the prior mean, by

Fig. 1. Map of New Zealand District Health Boards.

equation (2), and to shrinkages close to one. Furthermore, by equation (6), shrinkages increase in any given stratum as person-years at risk get smaller. The relatively uninformative Daniels (1999) uniform shrinkage prior of Christiansen and Morris was adopted for ζ: Following equation (6), defining $B_0 = \varsigma/(\varsigma + \varsigma_0) \sim uniform(0,1)$ yields a prior distribution for ζ with median ζ_0, chosen here as 10. In other studies, posterior inference seems insensitive to the choice of ζ_0 (Gatsonis & Daniels, 1999; Young et al., 2006). This also proved to be the case here for trial values of ζ_0 between 1 and 20. Additionally, allowing ζ_0 to vary by DHB based on an uninformative prior produced a less satisfactory model (larger deviance information criterion) than the constant ζ_0 models used for this work.

A priori, following Young et al. (2006), we expected interaction of age and income, sex and income, and (perhaps for 2001–2004) ethnicity and income as predictors of the mortality rate. Thus the two components of the regression hyper-parameters in equation (3) for the most complex prior model were

$$\begin{aligned} \beta_{1j} &= \left(\beta_{j,0}, \beta_{j,eth}, \beta_{j,inc}\right) \\ \beta_2 &= \left(\beta_{sex}, \beta_{age}, \beta_{age\times inc}, \beta_{sex\times inc}, \beta_{eth\times inc}\right). \end{aligned} \tag{7}$$

Prior models included some or all of the main effect and interaction terms described above. More complex models allowed terms $\beta_{j,0}$, $\beta_{j,eth}$, and $\beta_{j,inc}$ in the prior model to vary by DHB. Posterior estimates suggested that this was reasonable for $\beta_{j,0}$ and $\beta_{j,eth}$, but

Table 1
Deaths and person-years (total and by covariates) across the 21 District Health Boards (DHBs) in New Zealand, 2001–2004.

DHB (abbreviation)	Deaths		Person-years						
			Total	By sex (%)		By income quintile (%)		By ethnicity (%)	
	Unweighted	Weighted		Male	Female	Lowest	Highest	Māori	nMnPnA[a]
Northland (N)	1524	1895.8	179,700.4	48.2	51.8	29.8	12.5	21.6	78.4
Waitemata (Wt)	2925	3567.8	539,406.6	47.9	52.1	14.0	25.7	7.2	92.8
Auckland (A)	2016	2469.4	388,612.2	48.1	51.9	11.4	39.9	7.9	92.1
Counties-Manukau (CM)	1995	2467.0	350,939.2	48.0	52.0	14.6	23.3	15.1	84.9
Waikato (Wk)	2769	3364.5	416,855.8	48.1	51.9	21.8	17.0	14.0	86.0
Lakes (L)	822	1008.4	119,643.2	47.9	52.1	22.0	15.0	24.0	76.0
Bay of Plenty (BoP)	1920	2337.5	247,252.5	47.3	52.7	24.5	14.5	16.3	83.7
Tairawhiti (Tw)	477	585.1	53,720.3	47.7	52.3	29.0	11.3	35.2	64.8
Taranaki (Tn)	1086	1301.7	142,244.6	48.1	51.9	23.2	15.8	9.2	90.8
Hawkes Bay (HB)	1566	1895.2	192,061.3	47.2	52.8	23.6	12.5	15.6	84.4
Whanganui (Wg)	747	905.3	84,554.2	47.1	52.9	27.4	10.6	15.3	84.7
Midcentral (Mc)	1686	2052.9	208,111.6	47.4	52.6	22.6	14.0	10.3	89.7
Hutt (H)	1149	1385.9	172,666.0	48.2	51.8	14.7	22.2	11.1	88.9
Capital and Coast (CC)	1692	2035.8	321,258.7	47.7	52.3	11.1	36.3	7.9	92.1
Wairarapa (Wr)	405	490.8	56,174.0	48.0	52.0	23.9	12.9	9.1	90.9
Nelson Marlborough (NM)	1287	1552.7	179,774.0	48.2	51.8	23.6	11.8	5.4	94.6
West Coast (WC)	327	394.1	43,594.8	50.1	49.9	31.9	9.0	5.7	94.3
Canterbury (C)	3903	4678.1	618,370.4	48.0	52.0	19.7	15.5	4.7	95.3
South Canterbury (SC)	708	846.2	81,532.5	48.3	51.7	26.0	10.0	3.3	96.7
Otago (O)	1818	2169.2	243,727.9	47.9	52.1	23.2	12.2	3.8	96.2
Southland (S)	1074	1287.5	150,444.8	49.0	51.0	20.8	14.7	7.1	92.9

[a] nMnPnA = non-Māori non-Pacific non-Asian.

not for $\beta_{j,inc}$. However, one of the research questions to be addressed by this study includes variation in income inequalities by DHB. For this question, all three prior model terms were allowed to vary by DHB.

We used posterior mortality rate estimates from the models to calculate directly standardised rates and rate ratios, with 95% credible intervals (CIs). The distribution of the total eligible person-time was used as the standard population, i.e., for the fully-stratified analysis, 240 weights formed by cross-classifying the sex by five-year age group by income by ethnicity strata for all DHBs combined.

Thus, total person-time in each age, sex, ethnicity, and income (a,s,e,q) stratum was computed by summing over DHBs $P_{\cdot aseq} = \sum_j P_{jaseq}$. Weights were derived by dividing total stratum person-time by total NZ person-time $P = \sum_{aseq} P_{\cdot aseq}$ i.e., $w_{aseq} = P_{\cdot aseq}/P$. Standardisation over all strata (age–sex–ethnicity–income (ASEQ)-standardisation) for DHB j was calculated from posterior estimates of stratum-specific mortality rates in the usual way: $\lambda^*_{j.\mathrm{ASEQ}} = \sum_{aseq} \lambda_{jaseq} w_{aseq}$. For the partially-stratified case (e.g., by age and sex only), deaths and person-time were aggregated across unwanted strata, weights and posterior mortality rates calculated for the remaining strata, and standardisation proceeds in a similar manner to that described above e.g., $\lambda^*_{j.\mathrm{AS}} = \sum_{as} \lambda_{jas} w_{as}$.

The main results reported here are based on data that were fully cross-classified by DHB, sex, age, income and ethnicity, with all main effects included and with interaction terms for income with age, sex and ethnicity, and standardised by: sex, age, income and ethnicity when calculating overall DHB mortality rates; sex, age and income when calculating ethnic-specific rates by DHB; and sex, age and ethnicity when calculating income-specific rates by DHB. It was also of interest to see how much adjustment for ethnicity and income changed overall DHB rates, and to determine the impact on ethnic rates of not adjusting for income (an intermediary between ethnicity and mortality – not a confounder). For these extra models, it was necessary to aggregate the input data across levels of the variable omitted from modelling.

Software

Analyses and plots were done using the R environment (http://www.r-project.org) for statistical computation version 2.2.0 available from the Comprehensive R archive Network (CRAN) website (http://cran.r-project.org). Bayesian analyses used WinBugs 1.4, available from (http://www.mrc-bsu.cam.ac.uk/bugs/winbugs/contents.shtml), and the R bugs() function from the CRAN package R2WinBUGS version 2.0-4.

Linkage bias sensitivity analysis

As described above, we routinely use inverse probability weights to adjust for any linkage bias in the NZCMS. These weights were calculated with national-level analyses in mind – not regional comparisons. Thus, they do not allow for any regional variation in linkage success that is not explained by other variables used to generate the weights. It was not possible to generate such weights for either ethnic or income groups within each DHB.

For all DHBs except West Coast the estimated weighted sum of linked census-mortality records by DHB was within 2.6% of the actual number of deaths registered for that DHB (absolute average = 1.2%; Table 57 of Fawcett et al., 2008). However, the linkage bias adjusted number of deaths in the NZCMS needed to be increased by 8.6% to equal the actual number of deaths in the West Coast DHB. We used these crude weights to undertake sensitivity analyses.

Results

Table 1 provides a breakdown of actual person-years and deaths by DHB, and person-years by sex, income and ethnicity. A significant variation in population size across DHBs is evident in the 10-fold range in total person-years.

Posterior estimates of the prior model coefficients β_0 (the intercept) and β_{eth} (the ethnicity coefficient) from equation (3) suggested some variability by DHB (Fig. 2). A similar plot (not

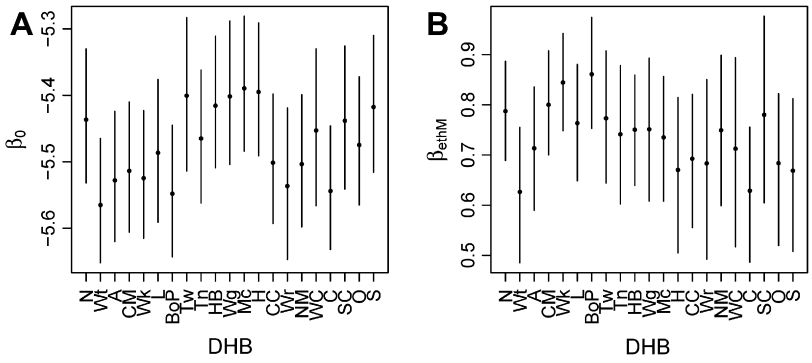

Fig. 2. Posterior estimates of prior model coefficients (vertical bars are 95% CIs) by DHB for (A) the intercept (β_0) and (B) ethnicity (β_{eth}).[1]

shown) for the income coefficient (β_{inc}) showed much less evidence for variability, and most rates and rate ratios reported here used a prior model with β_{inc} constrained to be the same for all DHBs.

Overall and social group-specific mortality rate variations between DHBs

Before addressing the main inequalities objective of this paper, we first present results for combined and group-specific mortality rates by DHB. Overall DHB standardised mortality rates for the fully-stratified analysis (Table 2; prior adjustment for and posterior standardisation by sex, age, ethnicity and income) ranged from 740 per 100,000 in Waitemata to 897 in Midcentral – a 21% higher mortality rate in Midcentral. Using a cleavage line of 824 per 100,000 (the median rate), six DHBs had significantly higher rates with 95% credible intervals above 824 (Tairawhiti, Hawkes Bay, Whanganui, Midcentral, Hutt, and Southland – and Northland nearly so, credible interval 819–896), and seven DHBs had significantly lower rates (Waitemata, Auckland, Counties-Manukau, Waikato, Bay of Plenty, Wairarapa, and Canterbury – Waikato (770–822) and Wairarapa (707–820) only just. Thus there are a number of DHBs with posterior CIs for overall standardised mortality rates that do not overlap. For a model that only adjusted for sex and age (Table_Annex 1), the DHB with the highest mortality rate (Tairawhiti, 1080 per 100,000) was 53% higher than the lowest DHB (Waitemata, 703). That is, additional adjustment for ethnicity and income narrowed the range of variation in DHB mortality rates by about 60% ([53% − 21%]/53%).

Considering ethnic-specific mortality rates, there were large differences in mortality rates between Māori and European/Other across all DHBs (Table 2). The relative position of European mortality rates by DHB, unsurprisingly due to their numerical dominance, followed that for the combined mortality rates. The patterning of Māori mortality rates showed some similarity. For example, Māori rates were notably higher in Northland and Tairawhiti, and notably lower in Waitemata and Canterbury, reflecting patterns in the European/Other rates. However, there were some differences. Most notably, Bay of Plenty had a high Māori mortality rate, whereas its European/Other mortality rate was comparatively low. Variation in mortality rates within low- and high-income quintiles roughly followed variation in overall mortality rates.

Variability in mortality rate ratios by ethnicity and income across DHBs

This divergence of European/Other and Māori rates in Bay of Plenty means that it had the highest Māori:European/Other rate ratio (2.4 (95% CI 2.1–2.6); Fig. 3a and Table 2). Waikato also had a notably high rate ratio (2.3 (2.1–2.5)). Waitemata and Canterbury had the lowest rate ratios (both 1.9 (1.6–2.1)) – significantly less than Bay of Plenty. However, there was considerable overlap in the CIs for other DHBs.

Fig. 3b plots posterior rate ratios and CIs for quintiles of income (Q1/Q5). In this case, and only this case, the prior model $\beta_{j,inc}$ was allowed to vary by DHB. There was some scatter in the central estimates of the rate ratios, but a close inspection reveals overlap (usually high) of all credible intervals. Thus, we conclude there is no strong evidence for variations across DHBs in mortality inequalities by income.

Comparing hierarchical Bayesian estimates with 'routine' estimates of standardised rates

Table 3 shows the routine directly standardised mortality rates for Māori and European/Other, for the hierarchical Bayesian estimates (i.e., as shown in Table 2) within strata of age by sex by ethnicity by income. As might be expected given the larger numbers of European/Others across all DHBs, there were only small differences in European/Other mortality rates between the HB and routine directly standardised estimates (4% or less difference). For Māori, however, there were marked variations between the HB and routine methods. For example, compared to the HB estimate of Māori mortality, the routine estimate ranged from 34% lower in Wairarapa to 50% higher in Hutt DHBs. The HB estimates of Māori mortality across DHBs ranged from 1321 to 1802 per 100,000, compared to a much greater range of 950–2457 per 100,000 for the routine estimates. That is, the HB estimator substantially reduced the range in observed empirical Māori mortality rates.

Consequently, the range across DHBs in the Māori:European rate ratios using the HB model estimates (1.86–2.38 to two decimal places) is considerably less than that for the routine directly standardised estimates (1.29–2.82).

Sensitivity analysis about linkage bias

Using crude weights to test for any residual linkage bias by region not already captured by the usual NZCMS linkage weights (see Methods), the most notable impact on results was an increase in the West Coast DHB mortality rate by 8.6%. Any

[1] The prior model included main effects for sex, age, income, and ethnicity and interaction terms for income with age, sex, and ethnicity. The underlying data were deaths within strata of DHB, sex, age, ethnicity, and income.

Table 2
Mortality rates per 100,000 (95% credible intervals) and rate ratios (95% credible intervals) by DHB from a model including sex, age, ethnicity and income.

DHB	Overall rate[a]	Māori rate[b]	nMnPnA rate[b]	Rate ratio Māori:nMnPnA[b]	Lowest income quintile rate[c]	Highest income quintile rate[c]	Rate ratio ncome[c]
Northland	856 (819, 896)	1760 (1610, 1920)	808 (770, 847)	2.2 (2.0, 2.4)	1030 (956, 1100)	677 (623, 738)	1.5 (1.4, 1.7)
Waitemata	740 (716, 765)	1320 (1150, 1500)	710 (687, 733)	1.9 (1.6, 2.1)	927 (874, 980)	555 (521, 589)	1.7 (1.5, 1.8)
Auckland	770 (741, 801)	1490 (1310, 1660)	732 (703, 761)	2.0 (1.8, 2.3)	1010 (940, 1080)	572 (533, 610)	1.8 (1.6, 2.0)
Counties-Manukau	790 (759, 819)	1650 (1490, 1810)	744 (715, 775)	2.2 (2.0, 2.4)	988 (924, 1050)	615 (575, 660)	1.6 (1.5, 1.8)
Waikato	795 (770, 822)	1710 (1570, 1870)	745 (718, 773)	2.3 (2.1, 2.5)	1010 (953, 1070)	599 (560, 639)	1.7 (1.5, 1.8)
Lakes	812 (765, 860)	1630 (1460, 1820)	769 (722, 816)	2.1 (1.9, 2.4)	1050 (963, 1140)	609 (554, 667)	1.7 (1.5, 1.9)
Bay of Plenty	767 (736, 797)	1700 (1550, 1880)	716 (686, 747)	2.4 (2.1, 2.6)	967 (905, 1030)	612 (568, 660)	1.6 (1.4, 1.7)
Tairawhiti	892 (826, 962)	1810 (1600, 2030)	844 (777, 918)	2.1 (1.9, 2.4)	1100 (986, 1230)	711 (635, 802)	1.6 (1.3, 1.8)
Taranaki	832 (791, 873)	1640 (1430, 1870)	789 (749, 829)	2.1 (1.8, 2.4)	1050 (971, 1130)	647 (591, 706)	1.6 (1.5, 1.8)
Hawkes Bay	878 (840, 917)	1740 (1560, 1930)	831 (795, 871)	2.1 (1.9, 2.3)	1080 (1010, 1160)	689 (635, 748)	1.6 (1.4, 1.7)
Whanganui	884 (832, 940)	1770 (1530, 2030)	837 (786, 892)	2.1 (1.8, 2.4)	1170 (1070, 1280)	663 (584, 736)	1.8 (1.6, 2.1)
Midcentral	897 (859, 935)	1750 (1550, 1960)	851 (815, 887)	2.1 (1.8, 2.3)	1130 (1060, 1200)	697 (644, 755)	1.6 (1.5, 1.8)
Hutt	892 (847, 937)	1630 (1400, 1860)	851 (809, 896)	1.9 (1.6, 2.2)	1120 (1030, 1210)	674 (620, 733)	1.7 (1.5, 1.9)
Capital and Coast	799 (766, 833)	1510 (1310, 1700)	762 (730, 796)	2.0 (1.7, 2.2)	1040 (960, 1120)	601 (561, 641)	1.7 (1.6, 1.9)
Wairarapa	763 (707, 820)	1440 (1170, 1700)	728 (674, 784)	2.0 (1.6, 2.3)	955 (859, 1050)	603 (537, 675)	1.6 (1.4, 1.8)
Nelson-Marlborough	801 (763, 839)	1590 (1360, 1840)	758 (722, 794)	2.1 (1.8, 2.5)	990 (917, 1060)	615 (565, 672)	1.6 (1.4, 1.8)
West Coast	840 (774, 911)	1620 (1320, 1930)	799 (736, 865)	2.0 (1.7, 2.4)	1070 (964, 1180)	642 (561, 726)	1.7 (1.5, 1.9)
Canterbury	758 (736, 780)	1350 (1170, 1530)	727 (706, 748)	1.9 (1.6, 2.1)	934 (886, 980)	576 (542, 614)	1.6 (1.5, 1.8)
South Canterbury	858 (806, 913)	1760 (1460, 2150)	810 (762, 860)	2.2 (1.8, 2.6)	1080 (991, 1170)	666 (598, 743)	1.6 (1.4, 1.8)
Otago	824 (790, 859)	1530 (1280, 1780)	786 (755, 818)	2.0 (1.6, 2.3)	1020 (953, 1080)	636 (585, 689)	1.6 (1.4, 1.8)
Southland	872 (827, 919)	1600 (1360, 1840)	834 (790, 880)	1.9 (1.6, 2.2)	1110 (1030, 1200)	675 (614, 738)	1.7 (1.5, 1.9)

[a] Overall rates standardised by age, sex, ethnicity and income.
[b] Māori and nMnPnA rates and rate ratios standardised by age, sex, and income.
[c] Income rates and ratios standardised by age, sex, and ethnicity.

shift in other DHB rates was well within their 95% credible interval.

Discussion

Main findings

Using a hierarchical Bayesian regression approach to model mortality rates in the 2001–2004 NZCMS cohort we found evidence for variability in ethnic disparities in mortality across regions within New Zealand. Ethnic mortality disparities, in rate ratio terms, were higher in Bay of Plenty and Waikato (both mixed metropolitan–rural areas with reasonably large Māori populations), and lower in Waitemata and Canterbury (both largely metropolitan populations). We did not find substantial evidence of variation in income mortality rate ratios by DHB.

Had we relied on routine direct standardisation methods (Table 3), we would have reported similar variability in European mortality across DHBS, but much greater variability in Māori mortality rates and in Māori:European rate ratios. That is, using HB methods for the "sparse data" problem we confronted made a substantial difference to the results. Not only are the HB estimates more conservative, given their ability to pool information across strata, but they have also been shown to have greater predictive accuracy (Gelman, 2006). That is, we would expect the HB estimates to be less affected by random variation and therefore to more accurately predict Māori mortality rates and Māori:European rate ratios across DHBs in the future (or past). Furthermore, since HB methods have good variance reduction properties (Best et al., 2005; Greenland, 2008), we would also expect CIs to be reliable measures of uncertainty in our estimates.

We also confirmed previous work showing marked regional variations in mortality across New Zealand (Pearce, 2007; Pearce & Dorling, 2006; Pearce et al., 2006). However, it is worth noting that the (empirical) methods used by these authors rely on ranking regions using measures of regional socio-economic status. In contrast, we found little evidence for regional variations in mortality by individual-level income. Using richer more finely stratified dataset, more realistic models, and better estimates of uncertainty appears to have considerably strengthened their conclusions. We extended this previous work in two ways. First, we found that ethnicity and income 'explain' about 60% of the sex and age-only adjusted variations in DHB mortality rates. Whilst we did not formally model the adequacy of DHB health funding formulae, this result suggests further research might be useful to improve current DHB population-based funding models that use sex, age, ethnic and deprivation (highly correlated with income) profiles of each DHB. Second, given the lower sensitivity of HB estimates to random variation and model misspecification, and the provision of reliable measures of uncertainty, we accurately documented for the first time variations in Māori mortality rates by DHB.

The hierarchical Bayesian method has one further advantage over traditional approaches, namely considerable potential for future investigation of geographical inequalities. For example, to tease out the dimensions that drive much of the observed regional variations in mortality inequalities, it might be helpful to extend the work reported here to an even finer level of aggregation e.g., ethnicity rate ratios by DHB over strata of sex, age and income. The richness of the NZCMS dataset could also be further exploited by more finely stratifying along any of several dimensions (e.g., geography), adding additional predictors, and including temporal information from earlier NZCMS datasets.

Strengths and limitations

The key strength of the NZCMS is its full population coverage and availability of all census data once linkages with mortality data are created. We also believe that hierarchical Bayesian analyses offer a conceptually appealing balance between observation and prior expectation. These models provide an approach to pooling information across strata, via their contribution to estimation of the prior model, without forcing relationships to be the same. For this reason they have good predictive capabilities, and give some protection against model misspecification. Furthermore, Bayesian shrinkage estimators have good variance reduction properties, particularly when sample size is small.

Within this project, but not reported here, we determined the impact on results of allowing ζ (the mortality rate variance hyper-

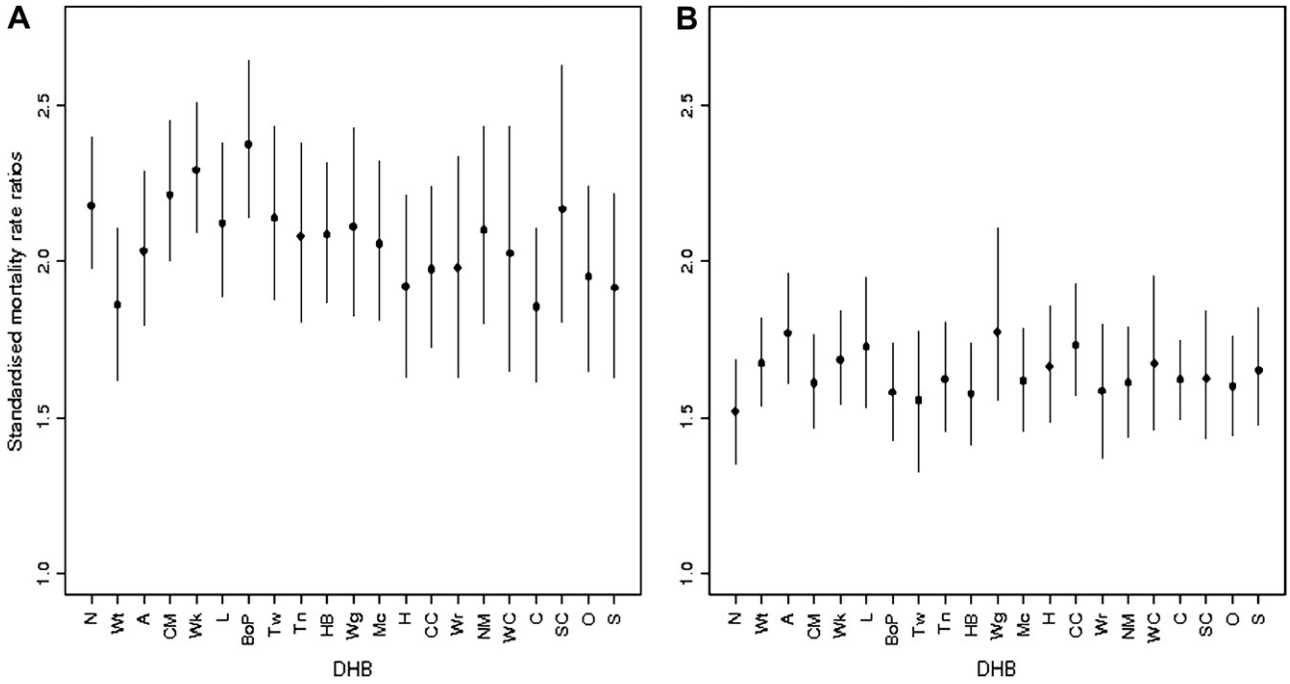

Fig. 3. Mortality rate ratios for ethnicity and income. In both cases the underlying data were deaths within strata of DHB, sex, age, ethnicity, and income, and vertical bars are 95% CIs. (A) Rate ratios for Māori compared to European/Other by DHB.[2] (B) Rate ratios comparing quintiles of income.[3]

parameter) to vary by DHB, thereby permitting greater shrinkage to the prior mean in data-poor DHB strata. We found little evidence for such variation, and hence no meaningful impact on the results as presented here. Other possible improvements to the modelling strategy might include: Allowing interaction terms involving income and ethnicity to vary by DHB, using previous NZCMS cohort results explicitly as informative priors or allowing temporal smoothing across cohorts/time; more extensive use of goodness of fit statistics for model selection; and more extensive use of existing or new covariate data e.g., neighbourhood deprivation, educational qualifications, and district-specific differences in the way health services are organised and delivered. We have strengthened evidence for the existence of regional variation in overall mortality rates, and found new evidence for ethnic inequalities in mortality rates, but explanations as to why those regional differences occur remain unclear. Future research will need to determine the key regional characteristics not modelled in this paper but which might help explain that variation.

In the future, it would also be sensible to directly include regional variations in linkage success in modelling. We also did not explicitly include sensitivity analyses (or imputation) for missing income values.

Implications

In New Zealand there is intense research and policy interest in health inequalities – particularly ethnic inequalities in health. This paper demonstrates that there is also a regional dimension i.e., even within ethnic and socio-economic strata, or adjusting for same, regional inequalities in mortality exist.

There was moderate variation in Māori and European/Other mortality rates by region. Often the rates varied together, resulting in no substantial variation in the Māori:European/Other mortality rate ratio by region: But not always. Of note, Waitemata and Canterbury had low European/Other mortality rate, but very low (relatively) Māori rates, giving rise to lower inequalities in mortality. Both regions largely comprise urban and suburban populations, with well-performing regional economies. Neither region has a high Māori population.

Explanations for the regional differences in both overall mortality and in ethnic inequalities in mortality will undoubtedly include those differences in socio-demographic factors not modelled in this

Table 3
Comparisons across DHBs of empirical and hierarchical Bayesian estimates of the directly standardised Māori and European/Other mortality rates (per 100,000) and rate ratios.[a]

DHB	European rates			Māori rates			RR Māori:European		
	Routine	HB	% Diff	Routine	HB	% Diff	Routine	HB	% Diff
Northland	813	808	1	1787	1760	2	2.2	2.18	1
Waitemata	710	710	0	1161	1321	−12	1.64	1.86	−26
Auckland	735	732	0	1181	1488	−21	1.61	2.03	−41
Counties-Manukau	735	744	−1	1567	1647	−5	2.13	2.21	−7
Waikato	739	745	−1	1622	1708	−5	2.19	2.29	−8
Lakes	764	769	−1	1760	1633	8	2.3	2.12	16
Bay of Plenty	707	717	−1	1765	1703	4	2.5	2.38	9
Tairawhiti	876	843	4	1871	1802	4	2.14	2.14	0
Taranaki	790	789	0	1420	1640	−13	1.8	2.08	−26
Hawkes Bay	839	831	1	1621	1735	−7	1.93	2.09	−14
Whanganui	839	837	0	1796	1767	2	2.14	2.11	3
Midcentral	862	851	1	1511	1750	−14	1.75	2.06	−29
Hutt	870	852	2	2457	1636	50	2.82	1.92	98
Capital and Coast	768	762	1	1356	1505	−10	1.76	1.98	−22
Wairarapa	733	728	1	950	1442	−34	1.29	1.98	−70
Nelson-Marlborough	758	758	0	1824	1592	15	2.41	2.1	28
West Coast	792	797	−1	1205	1616	−25	1.52	2.03	−49
Canterbury	727	727	0	1134	1349	−16	1.56	1.86	−35
South Canterbury	803	810	−1	2201	1757	25	2.74	2.17	49
Otago	792	786	1	1319	1535	−14	1.66	1.95	−30
Southland	850	834	2	1390	1598	−13	1.64	1.92	−31

[a] The hierarchical model includes sex, age, ethnicity and income, then directly standardizes by sex, age and income (i.e., same as Table 2). The empirical rates and rate ratios use observed stratum-specific rates directly standardised by sex, age and income. Percentage difference for rate ratios is calculated using excess rate ratios.

[2] Posterior standardisation used sex, age, and income.
[3] Posterior standardisation used sex, age, and ethnicity.

paper. But it is also likely that both migration selective by health status (Brimblecombe, Dorling, & Shaw, 1999; Connolly, O'Reilly, & Rosato, 2007; Norman, Boyle, & Rees, 2005) and regional variations in health services matter. Further research is required to understand the underlying drivers of those regional differences.

From a health service perspective, the results in this paper are thought provoking – given the remaining regional variations in mortality rates after adjusting for many of the factors in population-based funding formulae, are the existing population-based funding models capable of achieving geographic equity in health funding, even when fully implemented? The hierarchical Bayesian approach adopted for this work represents an important step towards addressing this question. On the basis of results presented here, a model for regional variations in mortality and mortality inequalities with good predictive capabilities appears to be a realistic goal. Future work could pursue improvements in this 'operational' model, and the development of models that explicitly incorporate details of, and are structurally related to, the funding process. Such models will provide a set of tools with which a variety of hypotheses about geographic funding equity can be explored.

Appendix. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.socscimed.2009.07.036.

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