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ORIGINAL RESEARCH ARTICLE

A Method for Comparing Health Inequality Impact Magnitudes, with an Illustration for Hypothetical Treatments of 1336 Diseases

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Abstract

Objective We aimed to facilitate the comparison and communication of magnitudes of health inequality impact across interventions for different diseases, and to indicate the potential range of such impacts.

Methods We propose rescaling the slope index of inequality to measure the health inequality impact as the change in the gap in total predicted quality-adjusted life-years between the least and most socially disadvantaged groups, with linear regression predictions used to account for effects on intermediate groups. We suggest reporting the inequality impact relative to the total health opportunity cost to facilitate comparison across interventions varying in scale and unit costs. We illustrated the approach with aggregate distributional cost-effectiveness analyses of hypothetical treatments for 1336 diseases in England. We approximated benefit shares for neighbourhood deprivation quintile groups using disease-specific hospital admissions. We tested between-group equality using generalised linear regression and constructed uncertainty intervals using Monte Carlo simulation. We assumed an equal total health opportunity cost and benefit-cost ratio of one, with alternative scenarios in a sensitivity analysis.

Results Health inequality impacts of hypothetical treatments ranged from −33.1% of the total health opportunity cost (inequality increasing) to +45.3% (inequality decreasing), and were ≤−5% for 1.6% of diseases, ≥+5% for 41.8% and ≥+20% for 1.6%. The impact was positively associated with the benefit-cost ratio and decreased when more deprived groups were assumed to incur proportionately more total health opportunity costs.

Conclusions Health inequality impacts can be compared using the change in the total predicted quality-adjusted life-year gap between the least and most socially disadvantaged groups as a proportion of the total health opportunity cost.

A Stata .dta file with simulation results for hospital admissions data on 1336 diseases and a code look-up table for the 155 mapped primary care conditions are available at https://doi.org/10.15124/b3453668-a5f5-47f6-a7ec-8894b1ec19ca.

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Key Points for Decision Makers

Magnitudes of health inequality impact across interventions for different diseases must be compared to identify cost-effective investments in health inequality reduction.

We show how to make these comparisons based on the change in the total predicted quality-adjusted life-years gap between the least and most socially disadvantaged groups as a proportion of the health opportunity cost.

We illustrate by simulating health inequality impacts of hypothetical treatments for 1336 diseases in England, which provides an indicative range of potential impacts.

In the context of a technology appraisal in England, a health inequality impact below 5% of the health opportunity cost might be classified as small, 5–10% as medium and above 10% as large.

1 Introduction

A distributional cost-effectiveness analysis (DCEA) evaluates the health inequality impact of an intervention as well as its cost effectiveness [1]. It can inform trade-offs between equity and efficiency, the prioritisation of socially disadvantaged groups that also face worse health prospects and the design of interventions to increase uptake among those groups. However, it is hard to compare magnitudes of health inequality impact between interventions for different diseases and to communicate those magnitudes to decision makers and stakeholders, who may be unfamiliar with inequality indices [2] and accustomed to evaluating effectiveness in quality-adjusted life-years (QALYs). Addressing this challenge is important to ensure DCEA delivers transparent and usable quantification of the health inequality reduction achievable through an investment, not merely providing qualitative information on the direction of any health inequality impact. In the UK, the National Institute for Health and Care Excellence recommends that evidence of a *substantial* health inequality impact be considered alongside an intervention's cost effectiveness, but it discourages a technology appraisal that uses equity weights—possibly derived from an estimated social welfare function—to make trade-offs between cost effectiveness and inequality impact [3]. Respecting this constraint requires use of a separate and interpretable measure of that impact.

DCEA usually focuses on the impact on health inequality between social groups. Reducing that inequality is an important health policy objective [3] that can stem from public concern about groups that are both disadvantaged socially (or economically) and more likely to experience illness and premature death [4]. These groups are often categorised by indicators of social disadvantage, such as area deprivation or ethnicity, which are routinely available in health datasets, allowing group health to be compared using a generic measure, such as quality- adjusted life expectancy (QALE) at birth. This population average is insensitive to an intervention for a specific patient group. For example, a gain of 1 QALY to each of 1000 patients potentially benefiting from an intervention would increase QALE by 0.000017 in a population of 60 million people. The impact on a between-group difference in QALE would be even smaller, and a tiny fraction of the baseline difference, which is around 11 QALYs between the least and most socially disadvantaged groups in England, for example [5]. The health inequality impact of an intervention depends on the number of people who can potentially benefit from it (scale) and the incremental cost per recipient (unit cost) as well as inequalities in intervention eligibility, uptake, effect and health opportunity cost arising from unrealised benefits of interventions competing for the same resources [1]. Cost is relevant because the magnitude and distribution of the health opportunity cost contribute to the net impact on health inequality. We therefore need a means of making even-handed comparisons of health inequality impact between interventions of different scale and unit cost.

This paper aims to facilitate the comparison and communication of magnitudes of health inequality impact across interventions for different diseases. It makes three contributions. First, it shows how to re-scale intervention-induced change in the slope index of inequality [6] to estimate impact as the change in the predicted total health (QALYs) gap between least and most socially disadvantaged groups, while keeping the slope index advantage of taking account of effects on middle groups. Second, the proposed method allows for differences in scale and unit costs of interventions by reporting the health inequality impact relative to health opportunity cost. Third, we illustrate the potential of the comparison method by using data on all hospital admissions in England to estimate potential inequality impacts of hypothetical new treatments for 1336 diseases and so indicating the range of impacts that may be obtained.

2 Health Inequality Impact Metrics

2.1 Health Inequality

Distributional cost-effectiveness analysis studies often stratify a general population into groups ranked in order of social disadvantage, and measure health inequality by the health

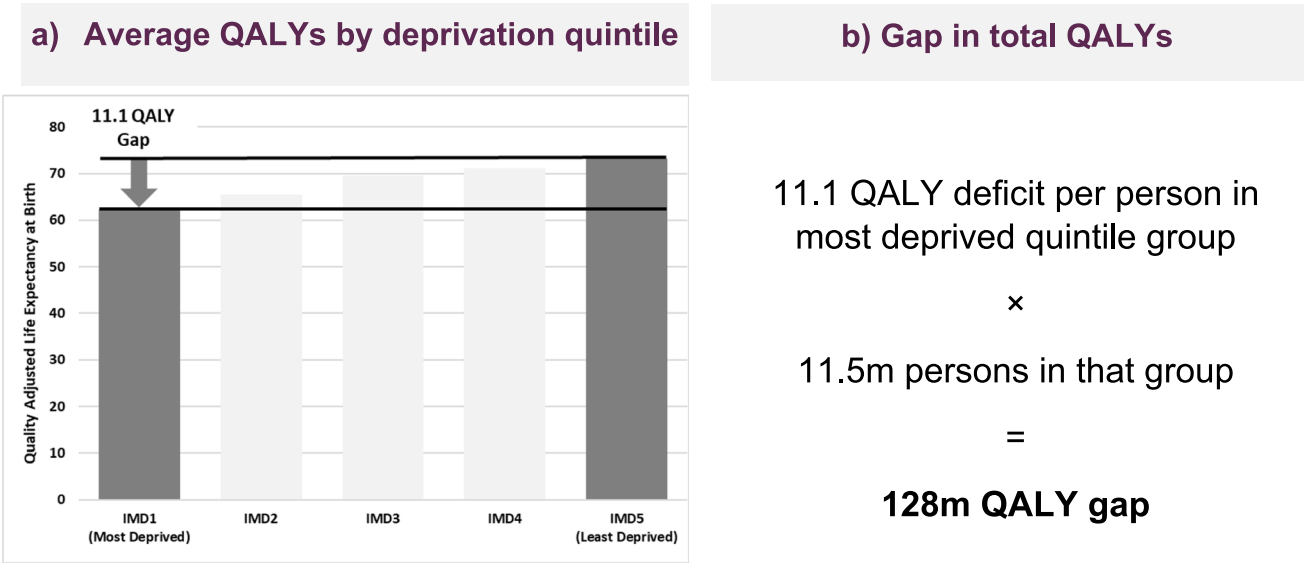

Fig. 1 Gaps in average and total quality-adjusted life-years (QALYs) between deprivation quintile groups in England, 2023. Based on Office of National Statistics mid-year population of England estimate for 2023 of 57 million (m) and estimates of quality-adjusted life expectancy by the Index of Multiple Deprivation (IMD) quintile group in 2017–18 [5]. Quality-adjusted life expectancy estimates are 62.2, 65.5, 69.5, 71.1 and 73.3 for the most to least deprived groups, respectively

gap between the least and most disadvantaged groups. For example, Fig. 1 shows the estimated gap in total QALYs between the least and most deprived quintile groups in England, based on neighbourhood deprivation.

This approach ignores the health of the middle groups. It would miss any health inequality impact of an intervention resulting from effects on the health of these groups. To avoid this limitation, we use the slope index of inequality (SII) [6], which is the estimated gap in *predicted* health between the extremities of the population ordered by social disadvantage. It is estimated from a linear regression of the mean health of the social disadvantage group j, h_j, on the cumulative fractional rank (at the mid-point) of that group, R_j:

$$h_j = \alpha + \beta R_j + \varepsilon_j, \tag{1}$$

where $h_j = \frac{1}{n_j}\sum_{i=1}^{n_j} h_{ij}$, h_{ij} is the health of individual i in group j of size n_j, $R_j = \frac{1}{n}\left(\sum_{k<j} n_k + \frac{n_j}{2}\right)$, $n = \sum_{j=1}^{J} n_j$ is the general population size and ε_j is an error term. The groups are ordered in decreasing social disadvantage. For example, if there were five equally sized groups, their fractional ranks would be 0.1, 0.3, 0.5, 0.7 and 0.9 from the most to least disadvantaged. The ordinary least squares (OLS) estimate of β is the SII, which is a scalar multiple of the generalised concentration index [7]. Note, Eq. (1) is not a model of health determination. It is a device to calculate the inequality measure—a descriptive statistic. Figure 2 shows the SII for QALE by social deprivation in England.

The SII reflects group differences in *mean* predicted health; differences in QALE, not QALYs, for example. The difference in *total* predicted health between the least and most disadvantaged groups is

$$\left(\hat{\alpha} + \hat{\beta}R_J\right)n_J - \left(\hat{\alpha} + \hat{\beta}R_1\right)n_1 = \hat{\alpha}\left(n_J - n_1\right) + \hat{\beta}\left(R_J n_J - R_1 n_1\right), \tag{2}$$

where $\hat{\alpha}$ and $\hat{\beta}$ are the OLS estimates of the respective parameters in Eq. (1). If the groups are constructed to be equally sized, such that $n_j = n/J\ \forall j$, then 2 collapses to the SII scaled by the population size and a factor determined by the number of groups:

$$GAP = \hat{\beta}\left(R_J - R_1\right)\frac{n}{J} = \hat{\beta}n\left(\frac{J-1}{J^2}\right). \tag{3}$$

For example, if there are five equally sized groups (as in our illustrative application), then $GAP = \hat{\beta}n \times 0.16$. This measure can be estimated directly as the OLS slope coefficient from a regression as (1) but with either multiplication of the left-hand-side variable by $\left(\frac{J-1}{J^2}\right)n$ or division of the fractional rank by that scaling factor.[1]

[1] *GAP* can also be estimated as the OLS slope coefficient, $\hat{\beta}_G$, from another linear regression,

$H_j = \alpha_G + \beta_G R_{Gj} + \varepsilon_{Gj}$, where $H_j = n_j h_j$ is group total health and $R_{Gj} = \frac{1}{n}\left(\sum_{k<j} n_k\right)\frac{J}{J-1}$ is the group fractional rank rescaled such that the most and least disadvantaged groups get ranks of 0 and 1. With five (equally sized) groups, for example, these ranks are 0, 0.25, 0.5, 0.75 and 1, from most to least disadvantaged.

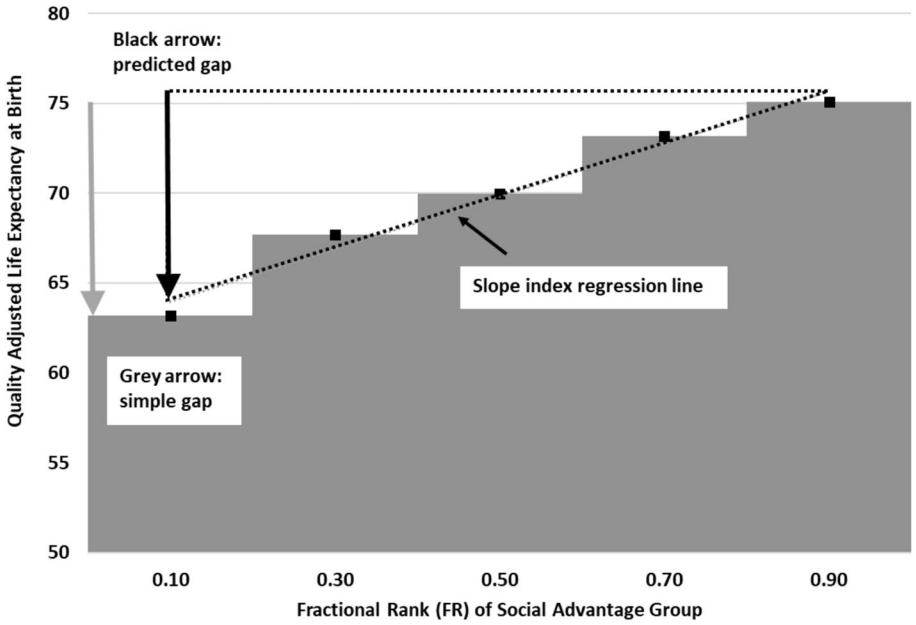

Fig. 2 Slope index of inequality measuring gap in predicted quality-adjusted life expectancy (QALE) between least and most deprived in England, 2023. the grey and black arrows indicate gaps in quality-adjusted life expectancy at birth and predicted QALE, respectively, between the least and most deprived quintile groups. Multiplication of each gap by the group population size gives the respective gaps in total quality-adjusted life-years. The slope of the regression line is the slope index of inequality: the gap in predicted QALE between the least and most deprived individuals in the population

The Electronic Supplementary Material (ESM) explains how to scale up the SII to measure inequality as the deficit in the predicted health of all individuals compared with that of the most socially advantaged. This is potentially useful where there are many population strata and the most and least disadvantaged groups are small and unequally sized. However, this measure is not as transparent as the predicted health gap between least and most disadvantaged groups, and it is harder to sense check against the gap in observed health. Furthermore, the predicted health gap can still be calculated in such cases, and it may be possible to combine sub-groups into least and most disadvantaged groups of approximately equal size.

2.2 Health Inequality Impact

The health inequality impact of an intervention can be measured by the induced change in *GAP*. This measures the intervention-generated narrowing or widening of the difference in total predicted QALYs between the least and most socially disadvantaged groups. Sensitivity to health effects on intermediate groups gives this measure of inequality impact an advantage over of the change in the raw difference in total (observed) QALYs between the two extreme groups.

We assume that DCEA simulation modelling has estimated the general population health benefit and health opportunity cost by social group, and calculated the corresponding net health benefits, each in QALYs.[2] If the policy concern is with inequality in health (not in discounted health), then an inequality impact should be based on the undiscounted net health benefit. Discounting of net benefit would normally be undertaken for the different purpose of assessing cost effectiveness, although equity issues arise even there [8].

The SII measures absolute health inequality—it is invariant to the addition of a constant to the health of all groups (or individuals). The *GAP* measure inherits this property. Consequently, the health inequality impact captured by the change in this measure can be estimated from the scaled SII of the incremental net health benefit (NHB) generated by an intervention. The average NHB of group j is the difference between its mean health (QALYs) with and without the intervention, $NHB_j = h_j(1) - h_j(0)$. This is the average health gain to group j from the intervention net of the average health opportunity cost incurred by that group.

Health inequality without and with the intervention could be estimated by the respective SII obtained from two linear regressions,

$$h_j(t) = \alpha_t + \beta_t R_{tj} + \varepsilon_{tj},\ t \in \{0,1\}, \tag{4}$$

where R_{tj} is the fractional rank of group j under intervention scenario t. Ordinary least square estimates of β_0 and β_1 are the SII without and with the intervention, respectively. Provided the intervention does not change the (social disadvantage) ranks, $R_{1j} = R_{0j}\ \forall j$, the change in health inequality can be estimated directly from a regression of the group-average NHB on the fractional rank:

$$h_j(1) - h_j(0) = \left(\alpha_1 - \alpha_0\right) + \left(\beta_1 - \beta_0\right)R_j + \varepsilon_{1j} - \varepsilon_{0j} = \gamma + \delta R_j + \upsilon_j. \tag{5}$$

[2] See the ESM for reviews of basic concepts of a cost-effectiveness analysis and a DCEA.

The OLS estimate of δ is the difference in the SII between the intervention and no intervention scenarios—a measure of the health inequality impact in QALYs per capita.

The change in inequality in total (not per capita) predicted health is equal to the gap in total predicted net health benefits. Assuming the intervention also does not change the group sizes, this is

$$\begin{aligned}&\left(\widehat{\alpha}_1-\widehat{\alpha}_0\right)\left(n_J-n_1\right)+\left(\widehat{\beta}_1-\widehat{\beta}_0\right)\left(R_J n_J-R_1 n_1\right),\\&=\widehat{\gamma}\left(n_J-n_1\right)+\widehat{\delta}\left(R_J n_J-R_1 n_1\right),\end{aligned} \tag{6}$$

where ^ indicates OLS estimates of the respective parameters. With equally sized groups, this reduces to

$$\Delta GAP=\widehat{\delta}\left(\frac{J-1}{J^2}\right)n. \tag{7}$$

That is, the scaled SII of the intervention's average NHB measures its impact on inequality in total health (QALYs). We label $-\Delta GAP$ the *health inequality impact*, which is positive if the intervention reduces inequality.

To compare impacts of interventions differing in scale and unit cost, the $-\Delta GAP$ generated by each can be divided by its total health opportunity cost (THC), i.e. QALYs potentially produced by the next best use of the resources consumed by the intervention. This *normalised health inequality impact*, which measures the inequality reduction (or increase) per QALY of opportunity cost, can be estimated by calculating each group's total net health benefit $TNHB_j = NHB_j \times n_j$, dividing it by the THC and regressing on a rescaled group cumulative fractional rank, $R_{Gj}=\left(R_j-\frac{n_1}{2n}\right)\frac{J}{J-1}$ (see footnote 1):

$$\frac{TNHB_j}{THC}=\gamma_G+\delta_G R_{Gj}+\upsilon_{Gj}. \tag{8}$$

The OLS estimate of δ_G multiplied by -1 is $-\frac{\Delta GAP}{THC}$: the estimated impact of the intervention on the difference in total predicted QALYs between the least and most disadvantage groups per health opportunity cost QALY. Dividing this measure by the marginal rate of transformation from expenditure to QALYs (k) and multiplying by 1 million gives the predicted QALY gap reduction per million of (money) expenditure, which can be used to compare efficiency of interventions in reducing inequality.

The normalised inequality impact can be estimated using group shares of benefit and cost without needing to calculate each group's $TNHB_j$. The ratio of this measure to opportunity cost can be written as:

$$\frac{TNHB_j}{THC}=\frac{THB_j}{THC}-\frac{THC_j}{THC}=s_j\times\frac{THB}{THC}-p_j=s_j\times BCR-p_j, \tag{9}$$

where THB_j and THC_j are the total health benefit and health opportunity cost for group j, respectively, $THC=\sum_j THC_j$, $THB=\sum_j THB_j$, $s_j=THB_j/THB$, and $p_j=THC_j/THC$. The benefit-cost ratio, $BCR=THB/THC$, is the inverse of the incremental cost-effectiveness ratio *(ICER)* multiplied by k. Using equivalence of ΔGAP with the gap in net health benefits, Eq. (9) and linearity of the regressions used to estimate GAP, we have:

$$\frac{\Delta GAP}{THC}=GAP\left(\frac{TNHB_j}{THC}\right)=GAP\left(s_j\right)\times BCR-GAP\left(p_j\right), \tag{10}$$

where $GAP(X_j)$ is the scaled SII of variable X_j.

Table 1 illustrates the calculations for a hypothetical treatment for sickle cell disease in England that would have a negative TNHB of -165 ($=5\times-33$) QALYs for the population overall but would generate positive TNHB in the two most socially deprived groups and so would have a positive health inequality impact ($-\Delta GAP$) of 174 QALYs, which is 26.1% of the health opportunity cost.

3 Illustrative Application

We illustrate application of the $-\Delta GAP$ measure and its utility for making comparisons across disease interventions by using it to quantify potential health inequality impacts of *hypothetical* new treatments for 1336 diseases in England. Application to so many diseases provides an indication of the range of potential impacts. We simulated impacts by estimating inequality in disease prevalence by social group using published data on hospital admissions and assuming the benefit of each new treatment would be proportional to prevalence by social group, with no inequality in each of treatment uptake, long-term health effect and health opportunity cost. We conducted a scenario analysis of sensitivity to assumptions about distributions of opportunity costs and treatment BCDs.

3.1 Data

Our main simulation was based on all inpatient (including emergency) hospital admissions in England in 2011/12 [9, 10].[3] We used Hospital Episodes Statistics data on 1336 International Classification of Disease, 10th Revision (ICD-10) three-digit disease codes [11].[4] We excluded censored

[3] The data are available at https://github.com/bitowaqr/dcea as part of this web tool https://shiny.york.ac.uk/dceasimple.

[4] As we aimed to count the number of people with a diagnosis rather than the number of admissions for a specific diagnosed condition, finished consultant episodes were related to an ICD code if the lat-

Table 1 Health inequality impact of hypothetical sickle cell intervention in England, QALYs

Social deprivation group (j)	Total health benefit (THB_j)[a]	THC (THC_j)[b]	TNHB ($TNHB_j = THB_j - THC_j$)	$TNHB_j - TNHB_5$	$-\Delta GAP_j = \widehat{TNHB}_j - \widehat{TNHB}_5$[c]
1 = Most	180	133	47	155	174
2	167	133	34	142	130
3	87	133	−46	62	87
4	41	133	−92	16	43
5 = Least	25	133	−108	0	0
Mean	100	133	−33	75	87
Health inequality impact					
$-\Delta GAP$					174
$-\Delta GAP/(5 \times THC_j)$[d]					0.261

QALYs quality-adjusted life-years, *THC* total health opportunity cost, *TNHB* total net health benefit

[a]Total health benefits are simulated on the simple assumptions of 1 QALY benefit per recipient and a total of 500 recipients with severe sickle cell disease receiving the intervention annually. Health benefit breakdowns by social group categorised by neighbourhood deprivation index quintiles are simulated using prevalence inequality alone, assuming no inequality in uptake or effect. We estimate prevalence inequality using primary care data from 2018, with shares of 35.92%, 33.49%, 17.34%, 8.15% and 5.10% from the most to least deprived groups, respectively. We assume that each group has a general population size of about 11.5 million summing to a total England population size of about 57.7 million, which was the UK Office for National Statistics estimate for 2023

[b]Health opportunity costs estimated based on a cost per recipient of £40,000, a health opportunity cost transformation rate (k) of £30,000 per QALY, and a flat gradient in health opportunity costs, see ESM

[c] $\widehat{TNHB}_j$ is the predicted TNHB for social advantage group j obtained from regression equation (5) scaled up by the population group size. ΔGAP_j is from Eq. (6), with group j in place of group 1 and $J = 5$

[d]Health inequality impact as a proportion of the total health opportunity cost over all groups

data for 143 very rare diseases and ICD-10 Chapters 20–22 for external factors (e.g. accidents) and special codes. We used quintiles of a neighbourhood Index of Multiple Deprivation (IMD) [12] to stratify the population into five equally sized groups from most deprived to least deprived. Admissions were categorised by these groups.

3.2 Methods

We used Eq. (10) to estimate the potential health inequality impact of a hypothetical treatment for each disease. We assumed equal uptake and equal average effect of each treatment across groups, such that group shares of QALY benefits (s_j) would equal shares of prevalence counts, which we estimated by IMD quintile group shares of disease-specific admissions in the Hospital Episode Statistics data. As these data include repeat hospital admissions within a year and more disadvantaged groups have higher rates of repeat hospitalisation for some diseases, admissions shares may overestimate prevalence count shares of these groups and so their shares of benefits from new treatments of these diseases, given group benefit is assumed proportional to prevalence.[5] We adjusted for this potential bias by using primary care data on 12 million patients from 1406 general practices that provide more accurate estimates of prevalence by deprivation group for 155 health conditions that can be matched to a subset of the 1336 disease categories in the Hospital Episode Statistics data used in the analysis [13]. For these 155 diseases, we estimated the health inequality impact from the primary care data and from the hospital admissions data. Then, we regressed the first set of estimates on the second (separately for positive and negative inequality impacts) and used the fitted regression to predict an adjusted inequality impact from the hospital-admissions estimate for all 1336 diseases (see ESM). The adjusted estimates are our baseline health inequality impacts.

After estimating the benefit shares (s_j) for the hypothetical treatment of each disease, we used a convenient regression like that in footnote 1 to estimate the scaled SII of this variable, which is $GAP(s_j)$. For the other two terms in Eq. (10), we assumed, for each treatment, the same benefit-cost

Footnote 4 (continued)

ter appeared in any of the 20 diagnosis fields. Consequently, episodes with multiple diagnosis codes were counted multiple times.

[5] Bias in the opposite direction because of higher likelihoods of a later or missed diagnosis among socially disadvantaged groups is possible. However, under the assumption that a new treatment does not change inequality in the diagnosis rate, it is appropriate to target the estimation of prevalence of diagnosed cases because that drives utilisation.

ratio (BCR) and an equal distribution of health opportunity costs, such that $GAP\left(p_j\right) = 0$. Consequently, the health inequality impact ($-\Delta GAP$) was determined only by inequality in benefit shares.

3.3 Base-Case Assumptions

Our base-case assumptions were, for each treatment-disease, (a) equal health opportunity cost shares, $p_j = 0.2 \forall j$, and (b) $BCR = 1$. The latter implies that each treatment is (just) cost effective; $ICER = k$. A larger BCR would increase the health inequality impact by producing a larger health effect per unit of cost and inflating the inequality in benefit shares (see Eq. (10)).

We assumed k = £30,000, in line with the technology appraisal decision threshold used by the National Institute for Health and Care Excellence. We interpret this as a context-specific health opportunity cost transformation rate that allows both for future long-term price decreases and for the rebate paid by the pharmaceutical industry to ensure that pharmaceutical cost growth in the UK is capped (see ESM). In this context, a BCR of 1 corresponds to both the ICER and k equal to approximately £30,000, although it can also fit cases with lower values of both parameters.

3.4 Uncertainty Intervals and the Scenario Analysis

We used Monte Carlo simulation to calculate uncertainty intervals around the scaled SII for adjusted-admission approximations of prevalence count (and benefit) shares, which determine the health inequality impact under the base-case assumptions. We took 1000 random draws from five group-specific Poisson distributions, with each event rate set to the observed admissions rate (number of admissions divided by population size) of the respective deprivation group. For each draw, we computed the scaled SII and used the percentile method to construct the 95% uncertainty interval. We used that interval to test the null of no social inequality in the prevalence of the respective disease.

We used group-level generalised linear models (Poisson with log link) of admissions counts to conduct two other tests of equality. The first regressed admissions on group indicators and tested equal admission shares of the most and least deprived groups. The second regressed admissions on fractional group ranks and tested the significance of the (exponentiated) rank coefficient. We produced a *conservative* set of inequality impacts in which the impact of an intervention was set to zero if the null of no inequality in the prevalence of the respective disease was not rejected by any of the three tests at the 5% significance level.

We conducted a sensitivity analysis using alternative BCRs of 1.5, 1, 0.75, 0.6 and 0.3. These values correspond to ICERs of £20,000, £30,000, £40,000, £50,000 and £100,000, respectively, if the health opportunity cost transformation rate (aka "threshold") used for monetising health effects (k) is assumed equal to £30,000. We also conducted a sensitivity analysis with respect to the assumption of equal health opportunity costs by considering three alternative scenarios in which cost shares were skewed (a) slightly toward more deprived groups (22%, 21%, 20%, 19% and 18%, for the most to least deprived groups), which we label *slight pro-poor*, (b) moderately in the same direction (24%, 22%, 20%, 18% and 16%), or *moderate pro-poor*, and (c) slightly in the other direction (18%, 19%, 2%, 21% and 22%), or *slight pro-rich*. See ESM for the rationale for these scenarios. With unequal health opportunity costs, the BCR has an indirect influence on the inequality impact because the distribution of net health benefits depends on magnitudes of health benefits and opportunity costs.

3.5 Results

Figure 3 shows the distribution of total admission counts of 1336 diseases for the most and least deprived quintile groups. Among the most deprived group, relatively more diseases have a high prevalence.

In the base case, potential health inequality impacts across the 1336 disease codes ranged from a reduction in the gap in total predicted QALYs between the least and most deprived fifths of the population equal to 45.3% of the respective health opportunity cost of the treatment (F11: mental and behavioural disorders due to use of opioids) to an increase in the gap of 33.1% (L36: other acute skin changes due to ultraviolet radiation). The inter-percentile range of these normalised health inequality impacts ($-\Delta GAP/THC$) of hypothetical treatments was from a gap reduction of 32.2% to a gap increase of 5.9%. The interquartile range was from a reduction of 11.9% to zero impact (a non-significant reduction of 2.6%). Impacts did not differ significantly from zero for 23.4% of diseases. Gap reductions (relative to cost) were $\geq$5% for 41.8% of diseases, $\geq$10% for 16.5%, $\geq$15% for 6.2% and $\geq$20% for 1.6%. Gap increases were $\geq$5% for 1.6% of diseases and $\geq$10% for 0.4%. Figure S1 of the ESM shows histograms of significant positive and negative health inequality impacts, respectively. Table S1 of the ESM provides normalised impacts for broad disease categories and Table S2 of the ESM lists the top and bottom ten diseases by normalised impacts.

Figure 4 plots normalised inequality impacts against inequality in prevalence (proxied by adjusted admission) shares between the most and least deprived groups. Panel a shows scenarios differing in cost effectiveness, while Panel b shows different health opportunity cost incidence scenarios (ESM). Compared with the base case (green), assuming lower cost effectiveness (higher ICER) and a relatively higher burden of opportunity costs on the poor each reduce the impact at any

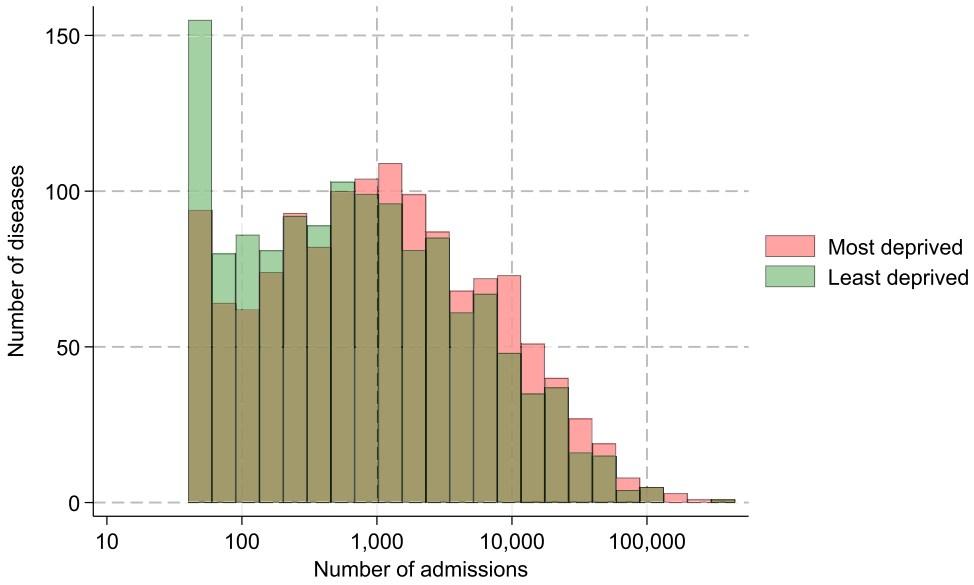

Fig. 3 Distribution of admission counts of 1336 diseases for the most and least deprived quintile groups in England, 2011. All inpatient hospital admissions in England in 2011–12 for 1336 International Classification of Disease, 10th Revision disease categories. The *horizontal axis* uses a log scale, with bin width of 0.176 representing a 50% increase. Low counts were censored to avoid the risk of disclosing sensitive information

level of inequality. The first result is because a less effective treatment per unit of cost closes less of the absolute QALY gap between the rich and poor. The second result is because the poor get a smaller net QALY gain when they incur more of the opportunity cost.

Figure S2 of the ESM provides a plot like Fig. 3a but reports health inequality impact per million pounds of expenditure by using a lower value of the assumed expenditure-health transformation rate of £15,000, as appropriate for evaluating existing treatments, not new treatments. Fig. S3 of the ESM shows simulations of health inequality impact based on primary care disease prevalence data for health conditions.

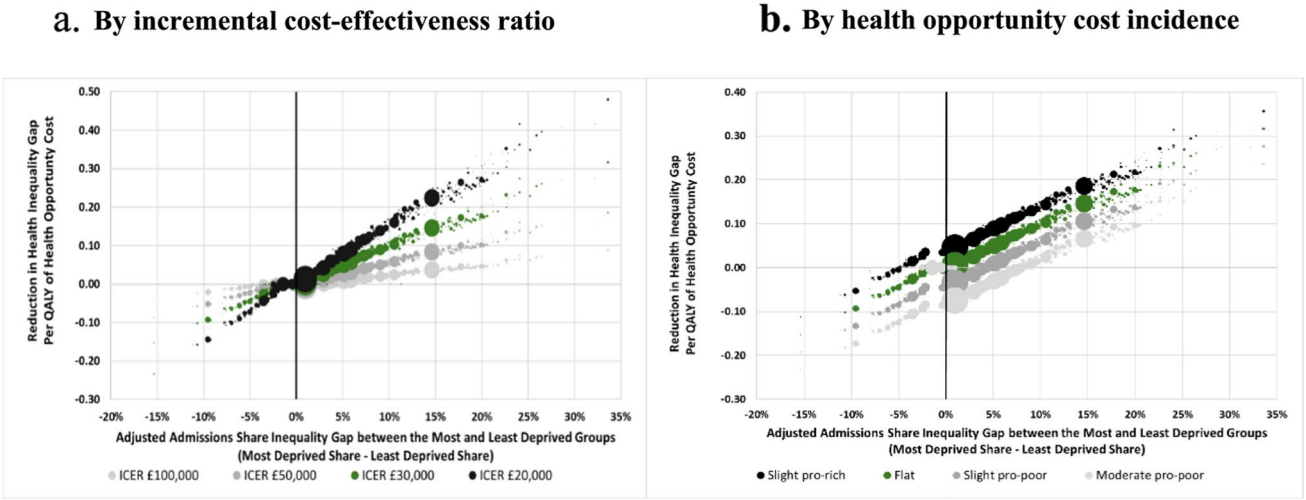

Fig. 4 Normalised health inequality impact against inequality in prevalence (proxied by adjusted admission) shares between most and least deprived groups for 1336 diseases, England 2011. *ICER* incremental cost-effectiveness ratio, *QALY* quality-adjusted life-year. The *y-axis* shows the health inequality impact as a proportion of the health opportunity cost, $-\Delta GAP/THC$, for each disease treatment. The *x*-axis shows, per disease, the inequality in prevalence count shares between the most and least deprived groups. Prevalence shares proxied by hospital admissions shares adjusted for repeat hospitalisations. The figure shows impacts for all 1.336 diseases, with impact set to zero when it is not significantly different from zero ($p \geq 0.05$), which creates the cluster of dots at zero for all scenarios (although only the colour of the last scenario in the legend, **a** ICER £20,000 and **b** Moderate pro-poor, is apparent when data points overlap). In **a**, we assumed equal health opportunity costs across groups and show results for benefit-cost ratios of 0.3, 0.6, 1 and 1.5, respectively, corresponding to ICERs of £100,000, £50,000, £30,000 and £20,000, respectively, assuming a health opportunity cost transformation rate of £30,000. This panel excludes one extreme outlier, L56: Other acute skin changes due to ultraviolet radiation, with a base-case impact of −0.33. In **b**, we fix the benefit-cost ratio at 1 and show results for four health opportunity cost incidence scenarios (see ESM).

For different levels of assumed cost effectiveness (BCR), Table 2 reports values of the positive normalised health inequality impact quantile function (Panel A) and its inverse (Panel B). For example, in Panel A, top row-middle column, 0.17 indicates that an inequality reduction of at least 17% of the health opportunity cost would be achieved by the 1% of treatments that would reduce inequality per QALY of opportunity cost most (assuming a BCR of 0.75 [ICER = £40,000]). In Panel B, the top row-middle column entry indicates that no treatments would achieve a normalised inequality reduction of 30%, while the cell immediately below indicates that 0.3% of treatments would reduce inequality by at least 20%. Table S3 of the ESM provides respective values for negative health inequality impacts and Table S4 of the ESM shows estimates without adjustment for repeat hospitalisation bias, in which case there is a wider range of positive impacts. Figure S4 of the ESM shows normalised impacts consistent with combinations of prevalence inequality and ICER values. Figure S5 of the ESM shows impacts before and after the adjustment for repeat hospitalisation. Finally, simulation results for all 1336 three-digit disease categories together with a code look-up table for our 155 mapped primary care conditions are available [14].

4 Discussion

4.1 Summary of Findings

We proposed a metric for reporting the health inequality impact of an intervention evaluated by a DCEA. It is the change in the gap in total predicted health (QALYs) between the least and most disadvantaged social groups that is calculated by re-scaling the intervention-induced change in the SII, a standard measure of social inequality in health. Equivalently, the metric is the scaled SII of the intervention's total net health benefit. Division by the health opportunity cost of the intervention incurred across the population gives the normalised health inequality impact per QALY of that cost. Measurement of inequality impact by change in the gap in *predicted* health between the top and bottom groups ensures sensitivity to (net) effects on intermediate groups.

Our illustrative application to hypothetical treatments for 1336 disease categories in England revealed that if all had a BCR of 1 and each was equally effective and imposed the same health opportunity cost across social groups, then the health inequality impact would range from a reduction in the (predicted) QALY gap between the least and most deprived fifths of the population equivalent to 45% of the population-wide health opportunity cost to a 33% increase in the gap relative to cost. The range of potential health

Table 2 Quantiles of the positive normalised health inequality impact for hypothetical disease treatments assuming different levels of cost effectiveness, England 2011

	BCR = 1.5 (ICER = £20,000)	BCR = 1 (ICER = £30,000)	BCR = 0.75 (ICER = £40,000)	BCR = 0.6 (ICER = £50,000)	BCR = 0.3 (ICER = £100,000)
A. Normalised inequality reduction achieved by treatments in the top					
1%	0.33	0.22	0.17	0.13	0.07
2.5%	0.27	0.18	0.13	0.11	0.05
5%	0.24	0.16	0.12	0.10	0.05
10%	0.19	0.13	0.09	0.08	0.04
20%	0.13	0.09	0.07	0.05	0.03
25%	0.11	0.08	0.06	0.05	0.02
30%	0.10	0.07	0.05	0.04	0.02
B. Percentage of treatments achieving a normalised inequality reduction above:					
0.30	1.6%	0.1%	0.0%	0.0%	0.0%
0.20	8.7%	1.6%	0.3%	0.0%	0.0%
0.15	16.5%	6.2%	1.6%	0.4%	0.0%
0.10	30.2%	16.5%	8.7%	4.0%	0.0%
0.05	54.3%	41.8%	30.2%	21.8%	4.0%

Panel A shows normalised health inequality impacts achieved by the P% of treatments achieving the largest inequality reductions per quality-adjusted life-year of opportunity cost. Panel B shows the P% of treatments achieving some threshold normalised inequality reduction. More precisely, it denotes the normalised health inequality impact by $X = -\Delta GAP/THC$, with x a particular value of this variable. The 1336 disease-specific estimates of this impact form an empirical distribution. Panel A shows values of x from this empirical distribution, such that $\Pr(X \geq x|X > 0) = p$ for $p \times 100 \in \{1, 2.5, 5, 10, 20, 25, 30\}$. Panel B shows values of $p \times 100$, such that $\Pr(X \geq x|X > 0) = p$ for $x \in \{0.3, 0.2, 0.15, 0.10, 0.05\}$

BCR benefit-cost ratio, *ICER* incremental cost-effectiveness ratio

inequality impacts becomes narrower if a less favourable BCR (lower cost effectiveness) is assumed. Positive health inequality impacts (inequality reducing) become smaller and negative impacts (inequality increasing) become larger in magnitude if more deprived groups, who use more healthcare, generally, and so may benefit more from alternative investments, are assumed to incur a larger share of health opportunity costs.

4.2 Strengths and Limitations

The main strengths of our proposed measure of health inequality impact are that (1) it is in QALYs, (2) it captures effects on all social groups and yet has an intuitive interpretation as a gap change, (3) it can be calculated from the distribution of net health benefits without needing to simulate the baseline distribution of health, (4) it is based on a widely used measure of health inequality and (5) it can be sense checked against the change in the gap in QALYs (not predicted QALYs), which is even more readily understood by non-specialists but, importantly, loses strength (2).

The measure can be reported as a proportion of the health opportunity cost, facilitating comparison between interventions of different scale and unit cost. Health opportunity cost provides a more appropriate denominator than net health benefit, which can be negative and close to zero, and total health benefit, which would not capture efficiency in reducing health inequality within a fixed budget. We suggest reporting health inequality impact by the reduction in the QALY gap per unit of cost rather than by the cost per QALY gap reduction. This is because the latter is potentially misleading—it looks like a conventional ICER but is not.

The main limitations of the measure derive from use of the SII. First, some studies prefer a variant of the SII derived from a non-linear relationship between health and social disadvantage ranks [6]. However, this leaves scope for overfitting and the subjective choice of specification to yield favourable DCEA results, and it would impede comparability across interventions [15]. Our objective was not to find the best-fitting statistical description of health differences across social groups but to propose an interpretable measure of inequality impact for consistent application in DCEA. A change in the rescaled SII is such a measure. Analysts can assess the data fit of the linear relationship given by Eq. (1) in any application and perform the sense check mentioned above.

Second, by utilising the SII, we measure the impact on *absolute* inequality, which can differ from the impact on *relative* inequality. Given that CEA aims to maximise the amount of health produced from constrained resources, considering impacts on differences in health levels is the most immediate distributional extension. Nonetheless, a relative inequality measure, such as the relative index of inequality (a scalar multiple of the concentration index [7]), could be used to check whether the direction of impact is the same for both types of inequality. It is more difficult to reduce absolute inequality, which requires that more disadvantaged groups get larger net health benefits from an intervention, than it is to reduce relative inequality, which only requires that net benefits be less unequal than the baseline distribution of health [16]. Decision makers must judge whether a reduction in relative inequality is sufficient to justify an investment or if that requires a reduction in absolute inequality.

Our illustrative application also has limitations. First, we only use three-digit ICD disease classification codes, whereas many new technologies focus on more fine-grained disease classification and clinical sub-groups. It is possible that a more granular analysis of disease categories would reveal larger and smaller inequality impacts. Hence, we may underestimate the range of potential impacts. Second, our assumption of equal uptake and long-term treatment benefit by social group will not hold for all new treatments. This may also cause underestimation of the range of impacts. Interventions with a lower uptake or smaller benefits for socially disadvantaged groups may increase health inequality, and so we may underestimate negative inequality impacts. Third, use of hospital admissions to proxy prevalence leaves scope for overestimating positive impacts and underestimating negative impacts if repeat admissions are more frequent in socially disadvantaged groups. While we tried to correct for this bias using matched primary care data, we cannot be sure how reliable the correction is, especially at high levels of inequality as there are relatively few matched conditions at these levels.

Given this illustration, which was based on old and approximate data as well as strong assumptions, was for hypothetical treatments, it does not inform of health inequality impacts of any actual treatments. For example, we found that hypothetical treatments for diseases afflicting newborn children would reduce health inequality (relative to cost) most, while equally cost-effective hypothetical treatments for cancers would be most inequality increasing (Table S1 of the ESM). Inequality impacts of actual treatments in these disease categories, which differ in cost effectiveness, will differ from those of the respective hypothetical treatments in magnitudes. Even the disease-category ranking of inequality impacts may differ for actual treatments.

5 Conclusions and Implications

Impacts on health inequality can be compared between interventions for different diseases in a manner that is grounded in the SII. We envisage that intuitive interpretation of our proposed measure of inequality impact as a between-group health gap reduction will appeal to decision makers aiming

to evaluate the return on investments in inequality reduction and to compare them across interventions for a wide array of diseases.

We hope our illustrative application to hypothetical treatments for diseases in England is useful in gauging the approximate range of health inequality impacts per unit of opportunity cost that might be expected from new treatments in different disease areas. The simulations may also help assess what might count as a sufficiently large and important impact to merit careful consideration in decision making. Rather than relying on inequality in prevalence to assess the potential inequality impact of an intervention, we recommend measuring the normalised impact per QALY of health opportunity cost, which depends on the ICER. For example, a prevalence inequality gap of 15% yields a normalised health inequality impact of about 15% if the ICER is £30,000, but only about 10% if the ICER is £45,000, 7.5% if the ICER is £60,000 and 5% if the ICER is £90,000. A simple approach would be to classify an inequality impact as *small* if less than 5% of the opportunity cost, *medium* if 5–10% and *large* if more than 10%. Using this tentative classification, our simulations for hypothetical treatments with an ICER of £30,000 (i.e. a BCR of 1) indicate that the impact would be *large* for about 16.5% of disease categories, falling to 8.7% with an ICER of £40,000, 4.0% with an ICER of £50,000, and zero with an ICER of £100,000 or more (Table 2 and Fig. S5 of the ESM).

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Declarations

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