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Title: Estimating social variation in the health effects of changes in healthcare expenditure

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Abstract

Background

A common aim of health expenditure is to reduce unfair inequalities in health. Whilst previous research has attempted to estimate the total health effects of changes in health expenditure, little is known about how changes affect different groups in the population.

Methods

We propose a general framework for disaggregating the total health effects of changes in health expenditure by social groups. This can be performed indirectly when the estimate of the total health effect has first been disaggregated by a secondary factor (e.g. disease area) that can be linked to social characteristics. This is illustrated with an application to the English NHS. Evidence on the health effects of expenditure across 23 disease areas is combined with data on the distribution of disease-specific hospital utilisation by age, sex and area-level deprivation.

Results

We find that the health effects from NHS expenditure changes are produced largely through disease areas where individuals from more deprived areas account for a large share of healthcare utilisation, namely respiratory and neurological disease and mental health. We estimate that 26% of the total health effect from a change in expenditure would accrue to the fifth of the population living in the most deprived areas, compared with 14% to the fifth living in the least deprived areas.

Conclusions

Our approach can be useful for evaluating the health inequality impacts of changing health budgets or funding alternative health programmes. However, it requires robust estimates of how health expenditure affects health outcomes. Our example analysis also relied on strong assumptions about the relationship between healthcare utilisation and health effects across population groups.

Introduction

Two central objectives of publicly funding healthcare systems are to improve population health and to reduce health inequality. In England, for example, there is a legal obligation to consider reducing population health inequalities in determining which services to include within the National Health Service (NHS) [1]. Whilst many studies have examined the impact of healthcare expenditure on population health [2]–[7], less is known about the impact on health inequality.

Conventional benefit incidence studies examine the average overall healthcare expenditure by sociodemographic group [8]. However, if policy makers wish to reduce health inequality, evidence on the distribution of the benefits of additional investment in healthcare (i.e. the changes in health outcome in each group as expenditure is altered) is required. These marginal benefits can be compared to investment in other programmes, such as education and social protection, or used to compare interventions within the health sector in terms of their impact on health inequality.

We propose a method for estimating the relationship between a change in overall health expenditure and changes in the social distribution of healthy life expectancy. This approach can estimate effects for a variety of sociodemographic characteristics simultaneously and can enable an analysis of the effects of expenditure on multiple dimensions of health inequality. We demonstrate this method with an application to England, using the results of a study of the marginal productivity of the English National Health Service (NHS) [9].

A further application is to use the estimated outputs in equity-informative cost-effectiveness analysis [10]. The health benefits accruing to different social groups from a new intervention can be compared against the social distribution of health benefits that would be expected as a result of general healthcare expenditure to determine whether the intervention would reduce health inequalities by more than existing services. The results from our method describe the social distribution of health opportunity costs of healthcare expenditure that can be used to inform healthcare decision making.

Methods

Overview

We describe a general framework for estimating a social distribution of health effects from marginal changes in healthcare expenditure. This framework uses the results of 'marginal productivity studies' that draw causal inferences about the relationship between health expenditure and health outcomes. Where the marginal productivity study does not directly estimate differences in marginal productivity between population groups, our framework shows how the estimated change in health from a given change in expenditure can be disaggregated indirectly. We illustrate the framework through an application to the English NHS, using evidence from a marginal productivity study for England [9], [11]. The social groups in our example are based on age, sex and socio-economic characteristics, but the method can in principle be applied to other variables considered relevant to assessing unfair differences in health. We hereafter refer to the characteristics that delineate the population groups as 'equity-relevant' variables.

Analytical framework

The results of marginal productivity studies of healthcare expenditure describe the total health effect (h^T) from a given change in expenditure. Our framework addresses the question of how the health effects from the change in expenditure are distributed between equity-relevant social groups. We express this formally as the share of the total health effect that is received by each group (denoted $p_{\boldsymbol{x}}$). Algebraically, the relationship between h^T and $p_{\boldsymbol{x}}$ can be written as $h^T = \sum_{\boldsymbol{x}} h^T p_{\boldsymbol{x}} = \sum_{\boldsymbol{x}} h_{\boldsymbol{x}}$, where $h_{\boldsymbol{x}}$ is the outcome of interest, i.e. the health change for each equity-relevant group $\boldsymbol{x}$.

The distribution of marginal health effects ($h_1, h_2, \ldots, h_{\boldsymbol{x}}$) could be estimated directly within a marginal productivity analysis. Including an interaction term between health sector expenditure and an equity variable (i.e. area-level socioeconomic deprivation) in the statistical model that links expenditure to outcomes, or estimating separate models for each equity-relevant group, would yield separate health effects for each group. This would require data on equity-related characteristics at the level of the unit of analysis (e.g., by disease area and geography). No existing marginal productivity studies have so far estimated effects in terms of equity-relevant groups. This could be due to the lack of information on the equity-relevant characteristics in the datasets used in marginal productivity analysis or the additional challenges posed by including interaction terms in statistical models estimating causal effects [12].

Indirect estimation of the distribution of health effects is instead possible if the marginal productivity study reports health effects in terms of a secondary factor (j) that can be linked to equity-relevant characteristics, such as healthcare facility type or disease area. The total marginal health effect can be defined as the sum of J subsidiary effects (h_j), such that $h^T = \sum_J h_j$. Each h_j can then be split between equity-relevant groups (denoted $h_{\boldsymbol{x}j}$), which are then

summed over all the secondary groups to obtain the total health effect for each equity-relevant group:

$$h_{\boldsymbol{x}} = \sum\nolimits_{J} h_{\boldsymbol{x}j} = \sum\nolimits_{J} h_j p_{\boldsymbol{x}j}$$

Where $p_{\boldsymbol{x}j}$ is the proportion of the health effect in category j accruing to equity-relevant group $\boldsymbol{x}$. The proportion of the overall health effect accruing to each group can then be obtained from the group-specific health effects and the total health effect via the formula $p_{\boldsymbol{x}} = \frac{h_{\boldsymbol{x}}}{h^T}$.

The proportions $p_{\boldsymbol{x}}$ provide the means to calculate the distribution of health effects for any given marginal change in healthcare expenditure (Δc). The change in expenditure is first converted into the total health effect ($h^{T|\Delta c}$) using the marginal cost of producing one additional unit of health (k). This summary measure of marginal productivity represents the rate at which health resources are converted into health at the margin. The group-specific effects ($h_{\boldsymbol{x}|\Delta c}$) are obtained by multiplying the total health effect by the respective proportion $p_{\boldsymbol{x}}$:

$$h_{\boldsymbol{x}|\Delta c} = {}^{\Delta c}/_{k}\, p_{\boldsymbol{x}} = h^{T|\Delta c} p_{\boldsymbol{x}}$$

A worked example demonstrating these calculations is provided in Appendix A (online appendix).

Data and assumptions

Applying the framework described above requires a reliable and valid estimate of health system marginal productivity. A number of these studies have been conducted since 2015 [9], [13]–[15], all of which employ an empirical strategy to exploit variation in health outcomes and health expenditure. This variation can be between geographical areas, over time or a combination of the two. Identifying the causal effect of health sector expenditure on health outcomes is, however, empirically challenging [16]. Reverse causality between outcomes and expenditure may be present, as historically poor health outcomes may lead to the allocation of extra health resources. An array of potentially unobservable environmental factors, with complex causal pathways, also determine health. For these reasons, studies investigating health system marginal productivity have adopted statistical methods that use instrumental variables to control for these unobserved factors.

A further challenge is that mortality data are most readily available as the basis for establishing a causal effect, but the impacts of health expenditure are not restricted to risk of death and for some diseases (e.g. hearing or vision) may be almost entirely in terms of health-related quality of life (HRQL). Marginal productivity studies have therefore developed methods for adjusting their mortality-based results to reflect HRQL effects.

To apply our framework, data linking the secondary factor to equity-relevant characteristics is needed. It is unlikely that data sources will able to validly allocate the health effects to equity-relevant groups directly, requiring assumptions to be made when they are used. For example, if the secondary factor is disease area, there is often evidence linking disease incidence or prevalence to equity-relevant characteristics. However, neither reflect differences in healthcare-seeking behaviour between social groups. Allocating the health effects in each disease area using these data may therefore overestimate the share of health for any groups who

are less likely to utilise services. This can be seen in the treatment of hepatitis C patients in the UK, for example, where uptake of services is lower in minority ethnic groups and intravenous drug users [17].

Information describing differences in healthcare utilisation in each disease area between equity-relevant groups does account for differences in uptake. However, simply using the distribution of utilisation to allocate the health effect assumes that each particular episode of care generates the same health benefit, regardless of the social characteristics of the recipient. For example, in the disease area of cancer using the socioeconomic distribution of surgical removal of tumours to describe the distribution of the health benefits from surgery would assume that every individual achieves equal benefit from undergoing surgery regardless of socioeconomic status. These assumptions can sometimes be relaxed, for example if there is evidence on the variation of health benefits from utilisation between groups. If a group with high socioeconomic status was found to yield greater benefits relative to lower groups then this can be used to weight its respective share of the health benefits.

The information linking the secondary factor with equity-relevant characteristics should describe how different social groups are affected by changes in health expenditure at the margin. Using the previous example, we would ideally want to know the distribution of additional (i.e. marginal) utilisation in each disease area following an increase in health expenditure. Trying to estimate this relationship between health expenditure and utilisation shares many of the complexities encountered during the analysis of health system marginal productivity, such as reverse causality. Using the distribution of average utilisation in the absence of information on marginal utilisation will assume that the former adequately

represents the latter. Empirical evidence on this topic is limited but indicates that the two distributions can differ [18].

Analysing inequalities

Inequality in marginal health effects can be explored with respect to each equity characteristic included in the analysis. There are numerous ways to summarise the extent of inequality in a distribution, and in general we desire those that encompass both the magnitude and direction of inequality (i.e. whether it favours the 'worst-off' or the 'best-off' and by how much). Where the equity-relevant characteristic divides the population into two groups, absolute and relative differences in health outcomes can be calculated directly. The same can be done for categorical variables if it is appropriate to consider specific pairwise comparisons. To compare across large numbers of groups or a continuous measure that can be ordered from 'worst-off' to 'best-off', a range of measures can be employed to summarise the differences (see Regidor [19] for an overview). These include regression-based measures such as the slope index of inequality (SII) and the relative index of inequality (RII), respectively.

The SII is the slope coefficient from a regression analysis, in which the health effect (h_x) or the proportion of the health effect (p_x) of an expenditure change is the dependent variable and the equity-characteristic of interest is the independent variable. The slope coefficient then describes the absolute difference in the share of health effects for a one-unit increase in the equity variable. To make this easy to interpret, it can be helpful to adjust the equity variable to achieve a 0-1 scaling. This allows the SII to be interpreted as the difference between 'best-off' and 'worst-off' group. If, for example, SII is estimated using income rank as the equity-relevant variable, then an SII of -0.2 would mean that the proportion of the overall health effect accruing to individuals at the bottom of the income distribution is 0.2 higher than for those at the top of

the distribution. The RII is obtained by dividing the SII by the mean of the dependent variable. In the example using income rank, an RII of -1 implies that individuals in the lowest income group accrue double the health from a marginal change in expenditure as those in the top income group.

It is also possible to calculate health effects in terms of a third variable not included in the marginal productivity or indirect analysis. For example, a geographical distribution can be imputed using the sociodemographic characteristics of each region. If low socioeconomic status individuals gain a higher share of health effects, for example, then the regions in which more socioeconomically deprived individuals live should also exhibit a higher share. This can be expressed as an index that is greater than 1 when the proportion of the health effect accruing to an area is greater than its respective share of the overall population, and vice versa. This is described further in Appendix B (online appendix).

Case study: Health effects of NHS spending in England

Our example uses the results of a study of the marginal productivity of the English NHS [9]. The authors used cross-sectional data on healthcare expenditure and mortality across 152 regional spending bodies ("Primary Care Trusts") in England in 2008, broken down by 23 broad disease areas (such as cancer or respiratory illness) called programme budgeting categories (PBCs). We use disease area as the secondary factor by which to link health effects to equity-relevant characteristics. An instrumental variables approach was used to account for endogeneity bias, and has been validated by similar results in subsequent studies [20], [21].

The econometric models estimated the elasticity of mortality with respect to healthcare expenditure: the percentage change in mortality given a 1% change in expenditure). Mortality

is measured in terms of years of life lost (YLL), the total number of life years lost in one year due to premature death for all diseases within a PBC. By combining the change in YLL across all disease areas from a given change in expenditure, the authors derived a marginal cost of £17,663 per life year. To account for gains to quality of life as well survival, further adjustments were made to obtain effects in terms of quality-adjusted life years (QALYs). The QALY is a measure of health that accounts for both health-related quality of life and survival by weighting the time spent alive according the individuals health state [22].

Health effects in terms of QALYs are estimated by applying the elasticities from the YLL equations to the "QALY burden" associated with each PBC (the annual total of QALYs lost in due to premature death and disability associated with all the diseases within a PBC). For example, a 1% change in NHS expenditure was estimated to yield a 1.6% change in years of life lost due to respiratory disease (PBC 11); applying this to the QALY burden of respiratory disease gives a change in QALYs of 17,981. This represents 29.7% of the overall change of 60,600 QALYs across all PBCs. The distribution of these QALYs over PBCs, which correspond to the quantities h_j in our framework, are given in Table 1. An overview of the methods used by Claxton and colleagues can be found in Appendix C (online appendix).

Table 1: Change in quality-adjusted life years (QALYs) generated from a 1% change in NHS expenditure in England by disease area

PBC #	**Disease area**	**Health effect (QALYs)**	**Proportion of total health effect**
	Total	*60,660*	1
11	Respiratory	*17,981*	0.2964

7	Neurological	*8,551*	0.1410
10	Circulatory	*8,453*	0.1394
5	Mental health	*7,469*	0.1231
4	Endocrine	*4,749*	0.0783
13	Gastrointestinal	*3,441*	0.0567
2	Cancers & tumours	*2,064*	0.0340
15	Musculoskeletal	*1,819*	0.0300
3	Blood disorders	*1,712*	0.0282
1	Infectious diseases	*1,229*	0.0203
9	Hearing	*1,098*	0.0181
17	Genito Urinary	*829*	0.0137
12	Dental	*533*	0.0088
8	Vision	*333*	0.0055
14	Skin	*152*	0.0025
20	Poisoning	*64*	0.0011
6	Learning disability	*54*	0.0009
21	Healthy individuals	*53*	0.0009
18+19	Maternity + Neonate	*18*	0.0003

Source: Claxton et al [10]

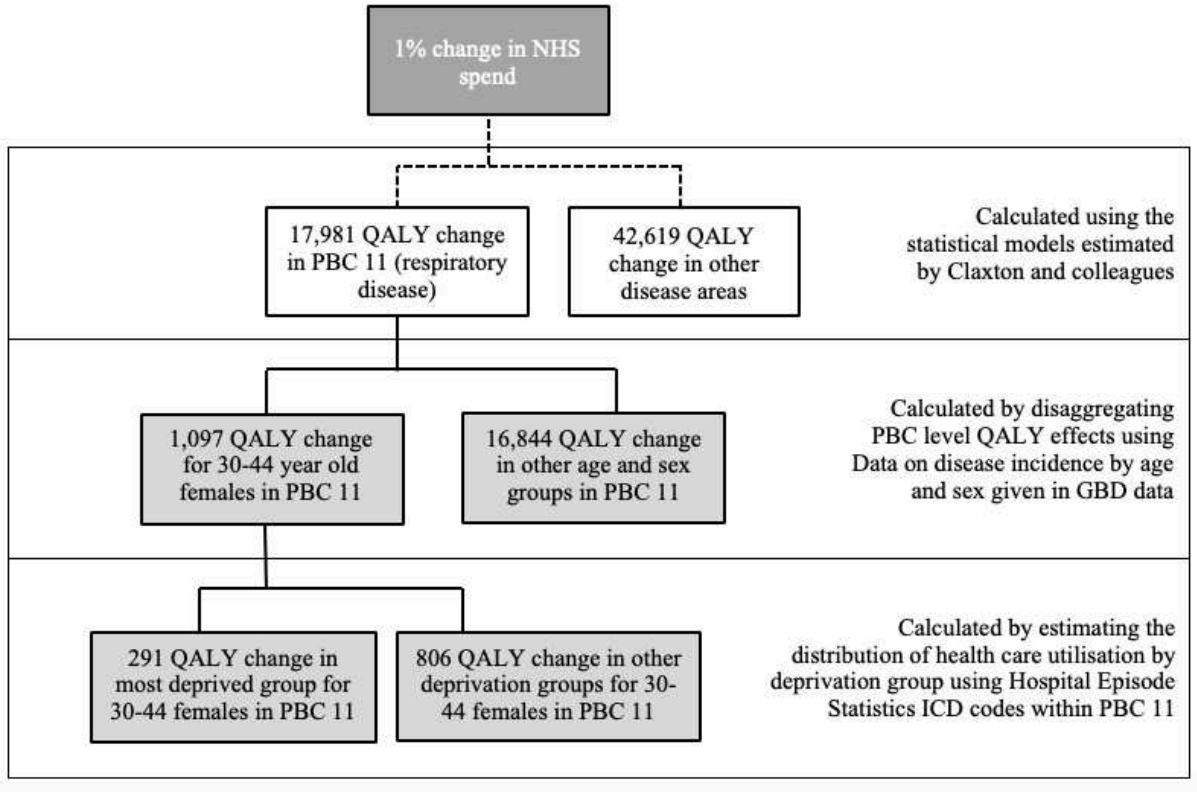
Health effects by social group

The social characteristics used in this example are age, sex and socioeconomic status. The latter is defined by the Index of Multiple Deprivation (IMD), an area-based measure of socioeconomic deprivation. We estimate the proportion of the health effect accruing to each subgroup in two steps, starting with age and sex first, and then socioeconomic status separately. The age and sex proportions come from a subsequent publication by Claxton and colleagues ,

in which the PBC-level effects are split by age and sex using disease incidence statistics for the UK, obtained from the World Health Organization's Global Burden of Disease Study [23]. For example, it was calculated that 6.1% of the incident population in the respiratory disease PBC are 30-44 year old females, meaning that the health effect accruing to this group is estimated to be 17,981x0.061=1,097 QALYs.

These health effects are then allocated to socioeconomic groups using the observed socioeconomic distribution of healthcare utilisation within each age, sex and disease area group. Summing over disease areas, we obtain the distribution of the overall health effect by age, sex and socioeconomic status. This process is summarised in Figure 1. Regional effects are also calculated by estimating weighting factors for each of the 326 local authorities (LAs) in England.

Figure 1: Influence diagram demonstrating how the health effects of a 1% change in healthcare expenditure for a single disease area are distributed by age, sex, socioeconomic status



Note: NHS = National Health Service; QALY = quality-adjusted life year; PBC = programme budgeting category; GBD = Global Burden of Disease; ICD = International Classification of Disease

Data and variables

Hospital Episode Statistics (HES) is a database containing information on all NHS funded activity in public and private hospitals. Socioeconomic status is assigned to each individual in terms of the deprivation level of place of residence. HES provides a comprehensive and nationally representative dataset for our analysis with full coverage of all ICD codes.

The primary unit of measurement in HES is the 'consultant episode'; patients whose care is transferred between consultants during a single stay in hospital may have multiple episodes.

We use HES data from 2012/13, the most recent available at the time of the analysis. Whilst these data do not temporally align with those used by Claxton and colleagues (mortality data for 2008-10 and expenditure 2008/9), they provided an up-to-date estimate of socioeconomic distributions.

The Index of Multiple Deprivation (IMD) is used as our measure of socioeconomic status. The IMD is a weighted index of 38 variables covering seven dimensions of deprivation (employment, income, education, health, crime, living environment, and housing/services) that is given to each of 32,482 geographical lower layer super output areas (LSOAs) in England. Each postcode belongs to an LSOA, giving each patient a deprivation score according to their postcode of residence. The 2004 version of the IMD is provided in HES for the financial year 2013/14 [24], which gathers the LSOAs (and their populations) into quintiles (five equally sized groups) to obtain a five-level socioeconomic status variable.

Disease is described by ICD codes included as diagnosis variables, of which up to twenty can be recorded for each episode. We convert the 4-digit codes to 3-digit codes, providing 1,562 diagnostic categories that are mapped to the 23 PBCs. We relate an episode to an ICD code if the latter appear in any of the 20 diagnosis codes. Consequently, episodes with multiple diagnosis codes will be 'counted' multiple times.

The HES inpatient dataset includes both day cases and overnight stays, encompassing a total of 19,578,568 unique episodes. We anticipated that the proportion of episodes with missing data would be small and primarily due to administrative or data entry errors. We therefore assumed that data are missing completely at random and removed observations with missing

age, sex or IMD quintile values from the sample, as well as those with no diagnosis codes. We further removed observations with sex unspecified.

Calculating the QALY distribution

We counted the number of episodes associated with each IMD quintile group within 24,992 subgroups (eight age groups, both sexes and 1,562 ICD codes). These collapse into 368 subgroups once ICD codes are mapped to the 23 PBCs. This is reduced to 320 subgroups as three PBCs are not allocated any health effects by Claxton and colleagues for reasons detailed in their report [9, p. 103]: Trauma and Injuries (PBC 16), Social Care (PBC 22) and General Medical Services (PBC 23). The count matrices are produced using Stata 12, with all subsequent analyses performed in R.

The counts were converted into proportions to obtain the distribution of utilisation by socioeconomic status within each age, sex and PBC group. Each of the 320 distributions is used to split its respective health effect. One group, 0-5 males in the maternity programme (PBC 18), had no episodes associated with it. We assumed a flat socioeconomic distribution for this group (which accounts for less than 0.001 of the total health effect).

In order to present the results and distributions by equally sized 5-year age groups we split the 10- and 15-year age groups from the GBD study into 5-year bands, using the respective population proportions from the ONS [25]. For example, 70-79 year-old males were disaggregated into the 70-74 and 75-79 bands according to their general population proportions, which are 0.56 and 0.44, respectively.

Analysing social inequalities

We analyse inequalities in the marginal health effects of healthcare expenditure changes by age, sex, socioeconomic status, PBC and region. Regional effects are calculated by estimating a weighting factor for each of the 326 local authorities (LAs) in England. The socioeconomic and sex distribution of each LA is used to predict its proportion of health opportunity costs: an LA will have a weighting factor greater than 1 when this proportion is greater than its respective share of the overall population and vice versa.

SII and RII are calculated to measure inequalities in the distribution of health effects. A larger negative SII or RII value indicates a greater proportion of the overall health effect accrues to more deprived groups.

Sensitivity analysis

Three types of sensitivity analysis were conducted on the results. First, we re-estimated results using the distributions of unique patients within each PBCs instead of episodes. Using episode counts assumes that every episode within each age, sex, and ICD group is associated with an equal probability of generating a QALY regardless of socioeconomic group, whilst using patient counts assumes that each patient has an equal probability of generating a QALY regardless of how many healthcare episodes they receive. We associated a patient with an ICD code if it appeared in the diagnosis codes of any of their ten most coded episodes (i.e. those with the highest number of diagnosis codes entered). A second sensitivity analysis was conducted by repeating our analysis using HES episode counts from the preceding two years to test whether there were differences in inequality over time.

Whilst HES provides comprehensive coverage of inpatient secondary care utilisation by age, sex, socioeconomic status and disease, it may not be the most appropriate data source from which to estimate socioeconomic distributions for some disease areas where secondary care represents a small proportion of healthcare activity. We were unable to access fully comparable data outside secondary care, and so performed a third sensitivity analysis that compares the socioeconomic gradient for the disease areas targeted in the Quality and Outcomes Framework (QOF) dataset to a matched subset of disease areas from HES. The QOF dataset [26] describes the prevalence of selected diseases in the practice population of general practitioners, which allows us to link socioeconomic variables by using the Attribution Dataset on GP Registered Populations to link to LSOA and to IMD. A full description of this sensitivity analysis is reported in Appendix D (online appendix).

Results

Descriptive statistics

Descriptive statistics for HES are reported in Table 2. In total, 119,569 (0.006%) observations were excluded from the sample. Another 51,344 were deleted as suspected duplicates, leaving a remaining sample size of 19,407,655 episodes covering a total patient population of 8,882,110.

Females accounted for a larger proportion of patients (56.1%) than males. A near-identical socioeconomic gradient in both episode and patient counts was found. The number of episodes attributed to each PBC and IMD quintile group are provided in Table A1. The ratio of episodes in the most deprived to least deprived groups ranged from 0.95 for cancers and tumours (PBC 2) to 2.87 for neonates (PBC 19).

Main findings

Table 3 demonstrates how the health benefits of a £50 million budget increase would be distributed between age, sex and socioeconomic subgroups using Claxton and colleagues' estimate of marginal NHS productivity of one QALY per £12,937. Of the 3,865 QALYs generated from the increase, nearly twice as many accrued to the most deprived fifth (1,019) as to the least deprived (537), whilst 25% of the health accrued to those under 20.

Table 2: Descriptive statistics for Hospital Episode Statistics 2012/13

Variable	**Patients**	**% Sample**	**Episodes**	**% Sample**
Total	8,882,110	100%	19,407,655	100%
Age				
0-4	999,334	11.3%	1,463,253	7.5%
5-14	363,592	4.1%	564,144	2.9%
15-29	1,183,033	13.3%	2,141,345	11.0%
30-44	1,427,015	16.1%	2,642,378	13.6%
45-59	1,520,374	17.1%	3,297,482	17.0%
60-69	1,204,898	13.6%	2,983,189	15.4%
70-79	1,143,281	12.9%	3,201,919	16.5%
80+	1,040,583	11.7%	3,113,945	16.0%
Gender				
Male	3,896,899	43.9%	8,826,364	45.5%
Female	4,985,211	56.1%	10,581,291	54.5%
IMD				
1 (most deprived)	2,090,295	23.5%	4,530,436	23.3%
2	1,799,620	20.3%	3,998,631	20.6%
3	1,804,243	20.3%	4,018,339	20.7%

Variable	Patients	% Sample	Episodes	% Sample
4	1,641,355	18.5%	3,571,730	18.4%
5 (least deprived)	1,546,597	17.4%	3,288,519	16.9%

Note: IMD = index of multiple deprivation

The distribution of health effects by deprivation quintile group is given in Figure 2. The most deprived fifth bore 26.4% of the overall health effect, compared to 13.9% for the most deprived fifth. This disparity is summarised with a SII of -0.15 and an RII of -0.77. For each IMD quintile group, females had a greater share of the health effect. However, the relative differences between deprivation groups were greater for men, with a RII of -0.80, compared to -0.75 for women.

The socioeconomic gradient was most pronounced in younger age bands; a large social gradient is clear from birth until the 40-44 band. RII values were consistently around -1.0 up to this age, indicating that the changes in health for the most deprived group is twice the magnitude of those for least deprived group. Thereafter disparities reduce to a minimal level: RII for the 85+ group is -0.06.

Table 3: Distribution of quality-adjusted life years by age and index of multiple deprivation (IMD) quintile group for a £50m change in the English National Health Service budget

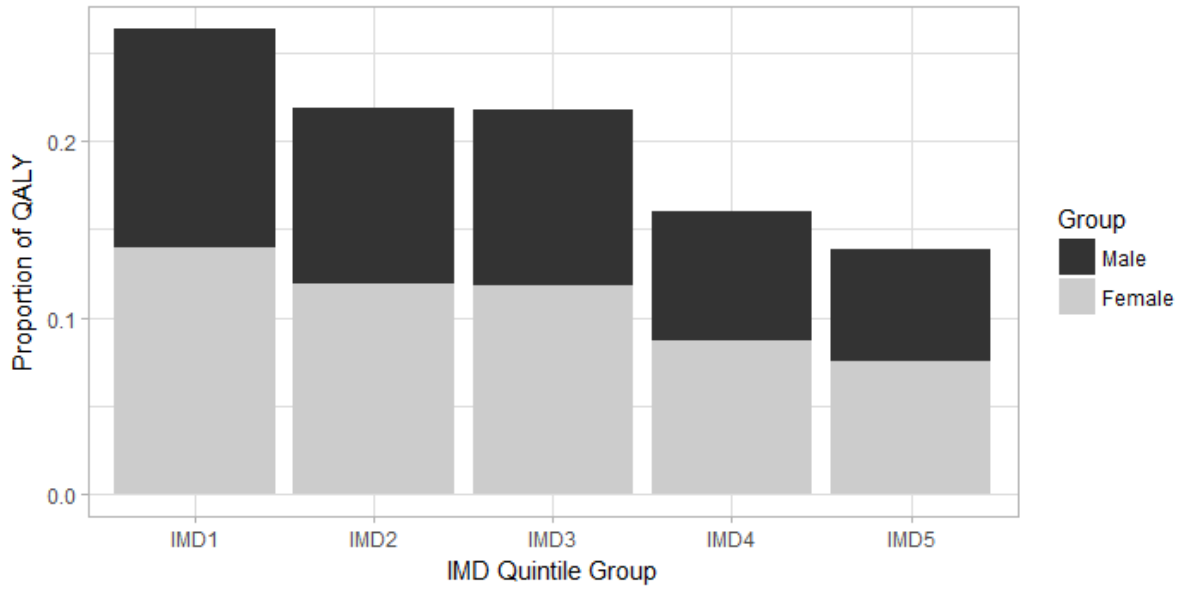
	IMD Quintile Group					
Age band	**1**	**2**	**3**	**4**	**5**	**Total**
0-4	105	81	79	51	46	**362**
5-9	44	36	36	25	24	**165**
10-14	43	35	35	24	24	**161**
15-19	74	59	58	37	32	**260**

20-24	82	65	64	41	35	**287**
25-29	83	66	65	42	35	**291**
30-34	48	39	38	24	20	**169**
35-39	46	37	36	23	19	**160**
40-44	51	41	41	25	21	**180**
45-49	74	62	61	43	37	**277**
50-54	66	55	55	39	33	**249**
55-59	58	48	48	34	29	**216**
60-64	58	51	51	45	38	**243**
65-69	54	47	48	42	35	**225**
70-74	47	43	43	41	36	**210**
75-79	39	36	36	34	30	**174**
80-84	24	24	24	25	23	**121**
85+	24	23	23	24	22	**116**
Female	***541***	***461***	***456***	***337***	***291***	**2,086**
Male	***478***	***387***	***386***	***282***	***246***	**1,779**
Total	**1,019**	**847**	**843**	**620**	**537**	**3,865**

Note:

1. IMD1=most deprived, IMD5=least deprived
2. An estimate of one QALY per £12,937 from Claxton et al. (2015) is used to predict the expected number of QALYs (£50m/£12,937 = 3,865).

Figure 2: Socioeconomic distribution of health effects from healthcare expenditure changes for English population



Notes:

1. IMD = index of multiple deprivation (1 = most deprived group, 5 = least deprived)
2. The differences in QALY effects between sexes should be treated with caution. This is because the larger effects for women reflect their levels of healthcare utilisation rather than any systematic differences in the healthcare services being affected by expenditure changes

Inequality within Programme Budgeting Categories

Table 4 shows the contribution of the each PBC to overall inequality in health effects. The respiratory programme, within which nearly 30% of health effects accrue, exhibits average levels of inequality, with an RII of -0.86. Mental health is one of the most unequal programmes with a RII of -1.28, and cancer the only pro-rich programme, with a RII of 0.08.

Inequality within regions

The regional weighting factors for English LAs are shown in Figure 3. LAs in the south and south east generally have a proportion of health effects relative to their population size, with

city-based authorities exhibiting larger shares: many London boroughs, as well as Manchester, Birmingham and Liverpool, have estimated weighting factors above 1.15, reflecting a higher share of disadvantaged areas.

Sensitivity Analysis

Results from all sensitivity analyses are reported in Table 5. The use of unique patient counts reduced socioeconomic inequality in the health effects of healthcare expenditure, with RII falling from -0.771 to -0.702. Negligible differences were found when using the HES datasets from 2011 or 2012, with the socioeconomic distribution of effects over IMD quintile groups staying consistent over time.

The inequality in health effects when using prevalence rates from QOF was fractionally smaller than when using utilisation statistics from HES. For the 37% of health effects covered by the diseases in the QOF data, RII is -0.905 when using QOF, compared with 0.922 when using HES.

Table 4: Inequality in quality-adjusted life year (QALY) effects by Programme Budgeting Category (PBC)

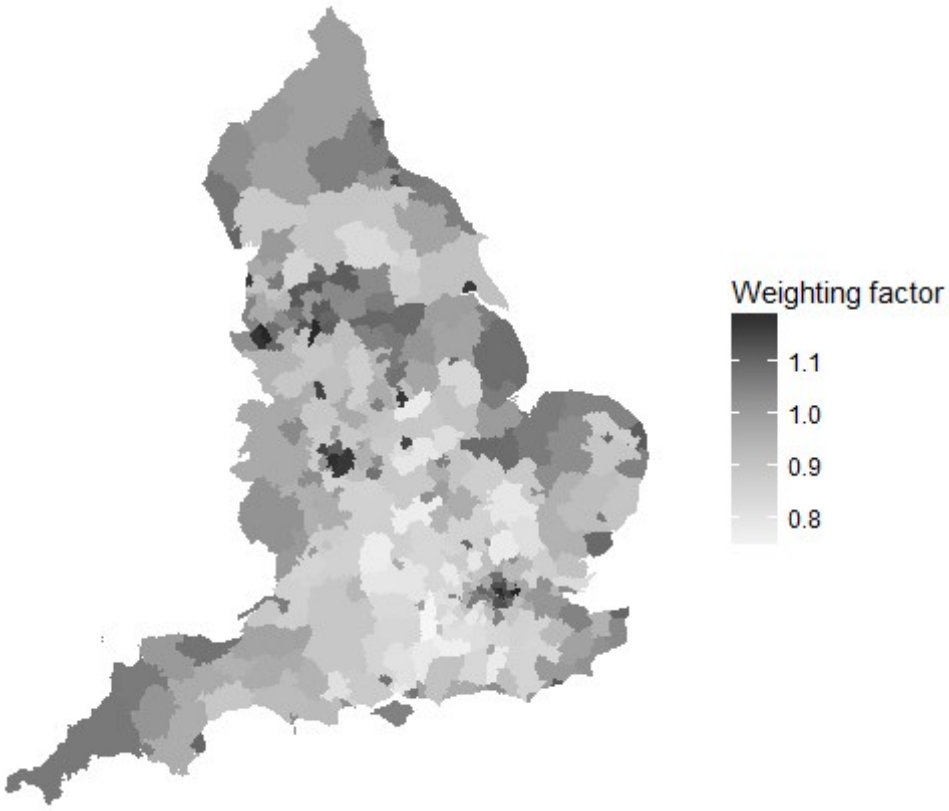
PBC	QALY proportion	QALYs from £50m spend increase	SII	RII
Total	**1**	**3865**	**-0.1542**	**-0.77**
Respiratory	0.297	1146	-0.0509	-0.86
Neurological	0.141	545	-0.0218	-0.77
Circulation	0.139	539	-0.0152	-0.54
Mental health	0.123	476	-0.0315	-1.28

Endocrine	0.078	303	-0.0129	-0.82
Gastrointestinal	0.057	219	-0.0071	-0.63
Cancers & tumours	0.034	132	0.0005	0.08
Musculoskeletal	0.030	116	-0.0021	-0.35
Blood disorders	0.028	109	-0.0047	-0.83
Infectious diseases	0.020	78	-0.0029	-0.72
Hearing	0.018	70	-0.0014	-0.40
Genito Urinary	0.014	53	-0.0015	-0.56
Dental	0.009	34	-0.0013	-0.74
Vision	0.005	21	-0.0004	-0.36
Skin	0.003	10	-0.0002	-0.45
Poisoning	0.001	4	-0.0002	-0.85
Learning disability	0.001	3	-0.0002	-1.11
Healthy individuals	0.001	3	-0.0003	-1.60
Maternity + Neonate	0.001	2	-0.0001	-1.31

Notes:

1. SII = slope index of inequality; RII = relative index of inequality
2. SII and RII measure inequalities in health effects within each PBC

Figure 3: Health effect weighting factors for English local authorities



Note: Weights greater than 1 indicate that health opportunity costs are greater than the expected share based on population alone

Table 5: Summary of sensitivity analysis around the socioeconomic distribution of health effects from healthcare expenditure: (i) previous years' HES episode counts, (ii) HES patient counts (iii) QOF prevalence data

	IMD Quintile Group					Inequality	
Data source	**1**	**2**	**3**	**4**	**5**	**SII**	**RII**
Complete analysis							
Episodes 2012/13	0.2636	0.2193	0.2180	0.1603	0.1388	-0.1542	-0.7711
Episodes 2011/12	0.2641	0.2194	0.2178	0.1606	0.1383	-0.1552	-0.7761

Episodes 2010/11	0.2651	0.2188	0.2184	0.1598	0.1378	-0.1568	-0.7842
Patients 2012/13	0.2601	0.2161	0.2138	0.1643	0.1457	-0.1403	-0.7015
QOF subset analysis							
Episodes 2012/13	0.1045	0.0829	0.0811	0.0565	0.0488	-0.0689	-0.9216
QOF 2013/14	0.1066	0.0848	0.0703	0.0616	0.0505	-0.0677	-0.9051

Notes:

1. IMD = Index of multiple deprivation; HES = Hospital episode statistics; QOF = Quality and Outcomes Framework; SII = Slope index of inequality; RII = Relative index of inequality
2. IMD1 = most deprived, IMD5 = most deprived
3. Episodes and patient counts estimated using secondary care data; QOF prevalence from primary care
4. The QOF subset analysis includes only health effects attributable to diseases covered by the QOF dataset (approximately 37% of the total health effect). As a result these rows sum to approximately 0.37 rather than 1.

Discussion

Main findings

Our analysis shows how the health effects of changes in government health expenditure can be disaggregated by equity-relevant social groups. Applying our framework to the results of a study of the English NHS, we found that expenditure changes imposed greater health impacts on the most socioeconomically deprived and were concentrated in younger age groups. The results support the conclusions of both Asaria et al. [27] and Barr et al. [28] that increases in NHS funding during the 2000s [29] likely contributed to a reduction in socioeconomic health inequalities.

Our case study results are underpinned by evidence produced by Claxton and colleagues on the relationship between local health expenditure and mortality, which they combined with other

data to estimate the marginal effects of NHS expenditure on population QALYs. A full list of these assumptions underpinning their results is given in Table 32 of their report [9, p. 83], upon which critiques and responses have subsequently been published [30]–[32]. When the plausibility of these assumptions was tested against expert clinical judgement, the results suggested that they are likely to be on the conservative side and will have led to an underestimate of marginal productivity (or an overestimate of the cost-per-QALY at the margin) [33]. Subsequent analysis of English data using different statistical models has also yielded consistent results over time [20], [21], and support the estimates used in our case study as being genuine causal effects. Sensitivity analyses suggest that our analysis is robust to quirks in healthcare utilisation specific to 2013, to the use of secondary care utilisation data rather than prevalence data or primary care utilisation data, and that our findings reflect consistent socioeconomic patterns by disease.

In the same way that the results of an analysis of marginal productivity can be used to estimate the health opportunity cost of health system investment decisions, the results derived from our framework can similarly be used to provide a distribution of health opportunity costs between equity-relevant groups. This is of particular use in "distributional" cost-effectiveness analyses that look at the differences in costs and effects by social group [10], [34], [35]. The metric of interest in this type of analysis is the distribution of net health benefit: the health benefits of a new technology minus the health opportunity costs of forgoing investment in other interventions. The adoption of a single intervention can usually be considered marginal (relative to the full set of resources) and will therefore not affect the marginal productivity of the health system. This means that the estimates generated by our approach can be employed in all subsequent economic evaluations that impose costs on the health sector budget. This is consistent with the way in which health opportunity costs are currently incorporated into the

approaches of agencies such as National Institute for Health and Care Excellence in England [36].

Limitations and assumptions

The framework proposed in this paper is needed due to the absence of health system marginal productivity studies that directly estimate health effects by social groups. Indirectly estimating this distribution requires us to combine the results of available marginal productivity studies with data on the social distribution of healthcare use.

The validity of the results is reliant on the quality of the original marginal productivity study. Analysis of marginal productivity presents a range of challenges with regards to estimating causal effects, namely availability of good quality data, endogeneity bias in the statistical model, and time lags between expenditure and health outcome. While broader application of this framework is limited by the availability of good quality studies that estimate the marginal productivity of healthcare expenditure, suitable estimates are increasingly available [13]–[15], [20].

Using healthcare utilisation data to disaggregate health effects assumes the health impact of one episode of healthcare is uniform across social groups. Although empirical work suggests that the health outcomes from healthcare are generally better for less deprived groups [37], little work has been conducted on the direct link between healthcare inputs and health outputs by socioeconomic group. Those in more deprived areas may be more likely seek care only when more severely ill and could therefore have a higher capacity to benefit from treatment, although treatment effectiveness may itself be reduced if patients present later. Furthermore, more affluent groups may be more effective at producing health from any given input of public

sector resource, due to lesser co-morbidity and greater ability to invest additional time and resources in recovery, care coordination and prevention. To the extent that the latter effect dominates, our results may overestimate the gradient in health effects.

Methods for fully characterising the uncertainty are not covered in this paper. Uncertainty over the proportions that characterise the social distributions of healthcare utilisation must also be combined with uncertainty around the health effect proportions from the marginal productivity analysis. In principle this could be propagated through all analytic steps via Monte Carlo simulation, but were not incorporated in our case study.

How representative the secondary factor is for capturing the impact of expenditure on outcomes requires consideration. We use secondary care utilisation data, and whilst many diseases are treated in secondary care, some disease areas or conditions are principally treated in primary care, such as asthma, or in specialist facilities, such as schizophrenia or other mental health conditions. We could not obtain primary care utilisation data that could test this hypothesis in our case study, although using primary care data from QOF indicates that results were largely comparable to secondary care utilisation. However, these prevalence data do not account for patterns of utilisation and would not capture the additional health benefits that sicker patients in more deprived groups obtain from multiple visits to primary care, for example.

Implications and further research

An important application of our results is their use in health technology assessment. The numbers in Table 3 are interpretable as the distribution of health opportunity costs that result from not funding £50 million worth of alternative health services. This distribution can help to inform decision-makers on what impact future interventions have on health inequality. This

could be through informal consideration or a distributional cost-effectiveness model [10], [34], in which our estimates can be combined with an equivalent distribution of health benefits generated by an intervention [38].

There is scope to improve our estimates by using better data with which to estimate the socioeconomic distributions of healthcare utilisation. For example, other datasets such as the Clinical Practice Research Datalink and the Mental Health Minimum Dataset could provide socioeconomic distributions of relevant conditions by age and sex in primary care and specialist mental health centres, respectively. Future research should also investigate the differences in health benefit achieved from receiving healthcare, which our analysis has assumed is the same for all socioeconomic groups. Lastly, similar analyses should be conducted for social care expenditure, as a comparison between the marginal effects of expenditures of health and social care can help inform resource allocation priorities with respect to health inequalities.

The framework demonstrated in this study provides additional evidence to decision makers on the distributional effects of health expenditure compared to traditional benefit incidence studies and can contribute towards the reduction of unfair population health inequalities.

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Conflicts of interest

The authors have no conflicts of interest to report.

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