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Equity Weights for Socioeconomic Position: Two Methods—Survey of Stated Preferences and Epidemiological Data

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ABSTRACT

Background: There is an implicit equity approach in cost-effectiveness analysis that values health gains of socioeconomic position groups equally. An alternative approach is to integrate equity by weighting quality-adjusted life-years according to the socioeconomic position group. **Objectives:** To use two approaches to derive equity weights for use in cost-effectiveness analysis in Australia, in contexts in which the use of the traditional nonweighted quality-adjusted life-years could increase health inequalities between already disadvantaged groups. **Methods:** Equity weights derived using epidemiological data used burden of disease and mortality data by Socio-Economic Indexes for Areas quintiles from the Australian Institute of Health and Welfare. Two ratios were calculated comparing quintile 1 (lowest) to the total Australian population, and comparing quintile 1 to quintile 5 (highest). Preference-based weights were derived using a discrete choice experiment survey ($n = 710$). Respondents chose between two programs, with varying gains in life expectancy going

to a low- or a high-income group. A probit model incorporating nominal values of the difference in life expectancy was estimated to calculate the equity weights. **Results:** The epidemiological weights ranged from 1.2 to 1.5, with larger weights when quintile 5 was the denominator. The preference-based weights ranged from 1.3 (95% confidence interval 1.2–1.4) to 1.8 (95% confidence interval 1.6–2.0), with a tendency for increasing weights as the gains to the low-income group increased. **Conclusions:** Both methods derived plausible and consistent weights. Using weights of different magnitudes in sensitivity analysis would allow the appropriate weight to be considered by decision makers and stakeholders to reflect policy objectives.

Keywords: cost-effectiveness analysis, equity, equity weighting, socioeconomic position.

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Introduction

In the developed world, the single strongest predictor of an individual's health is their position on the socioeconomic spectrum [1]. Those who are more disadvantaged are more likely to suffer from diseases and have higher mortality rates and lower life expectancies (LEs) [1–6]. It is therefore important that policies do not widen health inequities between socioeconomic position (SEP) groups. The importance of reducing health inequities is recognized globally [7]. Action to achieve health equity is considered an imperative by the World Health Organization. As a member state of the World Health Organization, Australia proposes to target people experiencing socioeconomic disadvantage so as to reduce health inequities [8].

Given health budget constraints, policymakers often use cost-effectiveness analysis (CEA) to inform resource allocation decisions across competing priorities. It is usual practice in CEA to

focus on “efficiency,” defined as maximizing health benefits for a given investment or minimizing cost for a specified outcome. Efficiency defined in terms of optimizing health gain is important, but usually policy objectives also include the reduction of health inequities. Although policy objectives embrace equity, the underlying assumption of economic evaluation is to value health gains of SEP groups equally, making it difficult to incorporate equity in a quantitative way.

One approach proposed in CEA is to integrate efficiency and equity by weighting quality-adjusted life-years (QALYs), the common outcome of interest in a CEA, according to characteristics of the people receiving them. These weights can quantitatively express the extent to which society is willing to trade overall health benefits to promote a more equitable distribution of health. Equity weighting of health gains to disadvantaged groups could be useful when there is a trade-off between improving total health and health equity. Furthermore, if a

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Published by Elsevier Inc.

<https://doi.org/10.1016/j.jval.2018.07.006>

program were cost-ineffective yet improved equity, the weights could help decision makers decide the level of concern for equity required for the program for it to be considered value for money. This could be particularly important for remote areas where service delivery can be expensive.

This study is focused on deriving equity weights for SEP. Currently, there is a lack of consensus on the algorithm for deriving equity weights [9]. Previous studies on the derivation of such equity weights have focused on stated preferences of members of the population or politicians. Discrete choice experiments (DCEs) have been shown to be useful for investigating preferences for health allocation [10,11]. Norman et al. [10], for example, combined various dimensions such as sex, smoking status, and income to derive equity weights. Nevertheless, separate equity weights for SEP by itself were not derived. In our study, we seek to derive equity weights for one dimension, SEP, using a DCE and the Norman et al. [10] methodology.

Health economics has been influenced more recently by the “decision maker approach” to economic evaluation, whereby the objectives of decision makers are emphasized in social welfare theory [12]. In this approach, the weighting of outcomes need not be preference-based as with other normative foundations (such as orthodox economics, which focuses on the market and responses to price signals, and extra-welfarism, which focuses on health-related quality-of-life preferences). The approach allows for the use of sources of valuation other than individual preferences such as reasoned argument [13]. Burden of disease estimates, for example, are well established and provide reliable estimates of health needs experienced across socioeconomic groups [14]. There is, therefore, a justification in economic theory for the use of robust, epidemiological data to derive equity weights.

This article presents two distinct ways of deriving equity weights for the most disadvantaged socioeconomic groups for use in economic appraisal. These weights could be applied to economic evaluations and priority setting exercises regardless of intervention or disease. Equity weights for SEP are derived first on the basis of epidemiological differences between SEP groups, and second on the basis of people's preferences using a DCE. Although reflecting different normative foundations in economics, the two methods of deriving weights could be considered complementary. We discuss their merits and the suitability of the resultant weights for use in different contexts.

Methods

Equity weights were derived for the purpose of adjusting the health gains of disadvantaged groups. If the health gains of a group are valued more highly, the equity weight for that group would exceed 1. The weights can then be used to adjust the QALY gains resulting from an intervention in that group to be relatively higher than without equity weights.

Calculation of Equity Weights Based on Epidemiological Data

Overview

We explored health inequalities across SEP quintiles in selected population health indicators, namely, disability-adjusted life-years (DALYs) and all-cause mortality. To calculate the weights for each indicator, two ratios were used: the ratio of quintile 1 (Q1) and the total Australian population and the ratio of Q1 and Q5.

Socioeconomic position

For the calculation of weights based on epidemiological data, SEP is represented by the Socio-Economic Indexes for Areas (SEIFA)

Index of Relative Socio-Economic Disadvantage as measured by the Australian Bureau of Statistics. SEIFA quintiles represent groups of individuals who live in similarly ranked areas, on the basis of a range of information such as income, qualifications, and occupation skills [15]. Each quintile comprises 20% of the population. The most disadvantaged group is SEIFA Q1.

Equity weights based on burden of disease

Burden of disease analysis measures the combined impact of fatal and nonfatal burden and considers age at death and severity of disease. The effects of different diseases are quantified in a consistent way and combined into a summary measure—the DALY. DALYs are a combination of the estimates of years of life lost because of premature death and years lived in ill health or with disability, to take into account the total years of healthy life lost from disease and injury. The estimates of burden of disease are well established and perhaps the most widely used summary measure of a population's health [14].

Equity weights based on the Australian burden of disease estimates in 2011 [16] were calculated as a rate ratio using the following formulas:

Equity weight A

$$= \frac{\text{Age standardized rate of total DALY burden Q1}}{\text{Age standardized rate of total DALY burden Australia}},$$

$$\text{Equity weight B} = \frac{\text{Age standardized rate of total DALY burden Q1}}{\text{Age standardized rate of total DALY burden Q5}}.$$

Equity weights based on all-cause mortality rates

All-cause mortality is all deaths in a population irrespective of cause. Australian mortality rates were obtained from the Australian Institute of Health and Welfare [17]. Mortality rates were calculated using the following formula:

$$\frac{\text{Number of deaths registered in 2014}}{\text{2014 population}} \times 100,000.$$

All mortality rates were directly age-standardized to the 2001 Australian standard population. These are revised every 25 years as recommended by the Australian Bureau of Statistics and the Australian Institute of Health and Welfare to align the revision cycle to represent the time span of a generation [18].

Equity weights based on all-cause mortality were calculated as a rate ratio using the following formulas:

$$\text{Equity weight C} = \frac{\text{Mortality rate Q1}}{\text{Mortality rate Australian population}},$$

$$\text{Equity weight D} = \frac{\text{Mortality rate Q1}}{\text{Mortality rate Q5}}.$$

Calculation of Preference-Based Weights

Overview

The second part of the study used a DCE survey designed to elicit population preferences regarding the allocation of health gain between hypothetical groups of potential participants. DCEs are widely acceptable in health economics for direct evaluation of different policy-relevant attributes of health care [19]. A random-effects (RE) probit model using a generalized estimation equation approach (i.e., population average model) [20] was estimated, and the results were converted to equity weights.

Discrete Choice Survey

Participants ($n = 727$) were asked to imagine they were helping the Health Department to choose between alternative hypothetical health programs that involved a choice between two attributes—"efficiency" (defined as increasing the LE of beneficiaries) and "health equity" (defined indirectly through the income level of beneficiaries). The decision was taken to construct a simple design, because it was important to maximize comprehension of the questions and meant that attributes and levels could be based on the literature rather than on qualitative focus groups. The average LE of high- and low-income groups in Australia was used, 81 years for the high-income group and 75 years for the low-income group [5]. This is consistent with Dolan and Tsuchiya [21] whereby LEs remained fixed throughout the choice sets. Two levels for income (high and low) and four levels of LE gain (1, 3, 6, and 10 years) were included. The survey contained 11 choice sets (Table 1). This resulted in nine levels of LE gain differences, for example, $1 - 3 = -2$. The choice sets were chosen from the combinations of predicted range in life-years lost associated with obesity-related diseases [22] (1, 3, 6, or 10 years), having regard to cognitive load, policy relevance, and survey feasibility. We chose to include all possible combinations of 1, 3, and 6 years, as well as the sets containing the lowest and highest values (10 and 1; 1 and 10) to derive weights for the largest possible difference in years. We did not incorporate all choice sets containing 10 years because we considered the subset chosen to be adequate for the range of difference in years desired. We also thought there would be less burden and better engagement with participants with fewer questions. Binary levels were used for each dimension, that is, a choice of increase in LE and income level from two options.

Participants were told that, on average in Australia, people from high-income groups live about 6 years longer than do persons from low-income groups. Each participant was asked 11 choice exercises in which income level and increase in LE were varied. To prevent position bias, the options were presented as A and B and were randomized. An example question is provided in Figure 1 (See Supplemental Appendix for full survey).

Table 1 – The choice sets contained in the survey.

Choice set	Income level	LE gain
1	High	1
	Low	1
2	High	1
	Low	3
3	High	1
	Low	6
4	High	1
	Low	10
5	High	3
	Low	1
6	High	3
	Low	3
7	High	3
	Low	6
8	High	10
	Low	1
9	High	6
	Low	1
10	High	6
	Low	3
11	High	6
	Low	6

LE, life expectancy.

This study used online methods to recruit people from around Australia. An online panel company (CINT Pty Ltd.) was engaged to send a link of the survey to people on their database until predetermined quotas for specific demographic characteristics such as sex, age, and education were achieved. Quotas were imposed in an attempt to achieve a demographically representative profile of the Australian adult population in 2011. Each survey respondent was paid a small amount depending on the time spent completing the survey. The survey was accessed via a Web link, enabling participants to complete the survey at their own convenience. A background to the questions and an explanation of the task were provided at the beginning of the survey. After completion of the 11 questions, there was the option for respondents to make further comments regarding the survey.

Analysis

A utility model (utility function 1) was used as per the methods of Norman et al. [10], in which the utility function j in the choice set s for survey respondent i was assumed to be as follows:

$$U_{isj} = \alpha \text{GAIN}_{isj} + \beta X'_{isj} \text{GAIN}_{isj} + v_i + \varepsilon_{isj}. \quad (1)$$

GAIN is the gain in total LE accruing to the hypothetical population group if the intervention was implemented and X_i is the income level of the hypothetical income group. GAIN was calculated by subtracting the stated gain in LE of the low-income group for a given question from the stated gain in LE for the high-income group for that same choice. GAIN had the following possible values: $-9, -5, -3, -2, 0, 2, 3, 5$, and 9 years. The error term ($v_i + \varepsilon_i$) comprises a person-specific error term and a conventional random error term distributed independently and identically normal. We considered a population average probit model using a robust method for estimating standard errors [23]. This approach implemented a person-specific error term v_i to take into account for the fact that choices made by an individual are not independent.

To account for the possible nonlinearity of utility with respect to gain in total LE, a more flexible utility function indicated as utility function 2 was considered:

$$U_i = \alpha \text{GAIN}_{isj} + \rho \text{GAIN}_{isj}^2 + \beta X'_{isj} \text{GAIN}_{isj} + \tau X'_{isj} \text{GAIN}_{isj}^2 + v_i + \varepsilon_{isj}. \quad (2)$$


By introducing the ρGAIN_i^2 term in utility function 2, the linearity of utility with respect to GAIN is relaxed. Also, by introducing the $\tau X'_{isj} \text{GAIN}_{isj}^2$ term, the assumption is relaxed that the change in total utility associated with the health gain being received by a different group of hypothetical respondents is independent of the total gain.


Utility function 1 assumes a linear link between gain and outcome, utility function 2 assumes a quadratic link between gain and outcome, and we also considered utility function 3 that assumes no parametric link between gain and outcome. As such, there is no specification of utility function 3. In utility function 3, GAIN values of $-9, -5, -3, -2, 0, 2, 3, 5$, and 9 were considered nominal values rather than an interval scale measurement. Each nominal value of GAIN was compared with a reference value of zero GAIN.

We compared performance (model fit) of the three different utility functions: linear, quadratic, and nominal using the Akaike and Bayesian information criteria (AIC and BIC) [24]. AIC and BIC are information-based criteria that assess model goodness of fit. When comparing AIC and BIC values, the model with the smallest AIC and BIC values is usually the preferred model.

Norman et al. [10] derived equity weights using the marginal rates of the substitution method, using GAIN as the value being compared. The value of an additional year of life for a hypothetical group was divided by the value of an additional year

☐ Q3 If you were asked to choose one of the two following programs, each of which would impact the health of 1000 people, which would you select?

 **Program A**
The people in this group have a high income.
Without the program, the people will live until they are 75.
The program would increase their life expectancy by 1 year.

 **Program B**
The people in this group have a low income.
Without the program, the people will live until they are 69.
The program would increase their life expectancy by 3 years.

☐ Program A

☐ Program B

Fig. 1 – Example of survey question.

of life for a reference group based on Australian averages. Nevertheless, because their hypothetical group had several dimensions, such as whether they were carers or smokers, this method was not suitable for our simplified DCE in which income level was the only group characteristic.

To derive our equity weights, we first compared the models using AIC and BIC statistics to determine the best fit. We then calculated the chance of the low-income group receiving GAIN by taking the exponential of the coefficients obtained from the RE probit, using GAIN = 0 as the reference category with a weight of 1. Weights were derived for differences in GAIN to the low-income group of -9, -5, -3, -2, 0, 2, 3, 5, and 9 years.

Observable Heterogeneity

To investigate heterogeneity in responses by the characteristics of respondents, we stratified the sample by sex, age, personal income, and education level. It was then possible to determine whether their responses differed by age group, for example, using multivariate models.

Results

Epidemiology Equity Weights

The weights based on epidemiology of population groups in Australia ranged from 1.21 to 1.54. Table 2 presents the equity weights based on the ratios of 1) burden of disease and 2) all-cause mortality for Q1 (lowest)/Q5 and Q1/the Australian population. Regardless of whether burden of disease or all-cause mortality was used, the derived weights were very similar. By construction, the weights are higher for the ratio Q1/Q5 than for the ratio Q1/the Australian population.

Table 2 – Equity weights based on epidemiological data.

Epidemiology	Quintile 1 vs. quintile 5	Quintile 1 vs. Australian population
Burden of disease	1.54	1.21
All-cause mortality	1.46	1.18

Note. The ratios were derived on the basis of actual Australian population numbers and not a sample, and therefore standard errors or confidence intervals are not necessary.

Preference-Based Equity Weights

Of the 727 people who started the survey, 710 completed all the questions, giving a completion rate of 98%. In the free-text responses, respondents gave reasons for the choices they made and indicated that they had a general understanding of the questions.

Table 3 compares the demographic details of the sample to the Australian population in 2011. The sample's representativeness differs by characteristic. The breakdown by sex and location across Australian states is close to the total population. People in the sample were generally older, more educated, and with a higher income than average.

For the choice sets in which the GAIN did not differ between the income groups, 62% to 66% of respondents chose the low-income group for the gains.

The results of the RE probit models for utility functions 1, 2, and 3 are presented in Table 4. In all utility functions, respondents were willing to discriminate in favor of programs with a greater health gain to the low-income group. The coefficient

Table 3 – Survey sample demographic characteristics and representativeness.

Variable	Sample (%)	Population (%)
Sex, female	52.0	51.1
Age (y)		
18–35	21.6	30.2
36–55	45.8	36.4
≥ 56	32.7	33.4
Education level		
High school	24.9	47.1
Trade, associate degree	33.1	30.6
Bachelor degree or higher	42.0	22.2
Income		
< \$32,000	34.4	51.4
\$32,000–\$64,999	29.3	28.8
\$65,000–\$103,999	26.2	13.0
> \$104,000	10.1	6.8
Location		
New South Wales	32.3	32.0
Victoria	27.2	24.9
Queensland	20.6	20.1
South Australia	8.2	7.2
Western Australia	9.6	11.0
Tasmania	1.3	2.2
Australian Capital Territory	1.0	1.6

Table 4 – Probit model results of the three utility functions.

	Utility function 1 (SE)	Utility function 2 (SE)	Utility function 3 (SE)
Constant	0.5539 (0.2226)*	0.5308 (0.2375)*	
GAIN (y) [†]	0.0758 (0.0039) [‡]	0.0755 (0.0039) [‡]	
GAIN ^{2§}		−0.0007 (0.0004)	
GAIN (nominal)			
GAIN = −9 y			−0.6585 (0.0478) [‡]
GAIN = −5 y			−0.6295 (0.0456) [‡]
GAIN = −3 y			−0.0445 (0.0269)
GAIN = −2 y			−0.4353 (0.0399) [‡]
GAIN = 0 (no gain)			(base)
GAIN = 2 y			0.2387 (0.0345) [‡]
GAIN = 3 y			0.2330 (0.0367) [‡]
GAIN = 5 y			0.4202 (0.0434) [‡]
GAIN = 9 y			0.5648 (0.0556) [‡]
Sex (reference female)	−0.0612 (0.0745)	−0.0646 (0.0744)	−0.0078 (0.0660)
Age (23–35, 36–55, > 55 y)	0.0592 (0.0503)	0.0645 (0.0502)	0.1383 (0.0351) [‡]
Education level (high school, trade, or university)	0.0080 (0.0486)	0.0069 (0.0486)	0.0447 (0.0442)
Personal income [¶]	−0.1407 (0.0365) [‡]	−0.1405 (0.0364) [‡]	
Personal income (nominal)			
<\$32,000			(base) = 0
\$32,000–\$64,999			−0.2107 (0.0990)*
\$65,000–\$103,999			−0.2987 (0.1007)*
>\$104,000			−0.4018 (0.1316)*
Wald χ^2 (df)	394.03 (5)	408.04 (6)	483.23 (13)
AIC	6600.5	6601.0	6488.6
BIC	6649.2	6656.7	6593.0

Note. Values are presented as means. Sex, age, education level, and personal income relate to the respondents' characteristics.

AIC, Akaike information criterion; BIC, Bayesian information criterion; SE, standard error.

* 5% level of statistical significance.

[†] Linear gain was used in utility weight functions 1 and 2.

[‡] 1% level of statistical significance.

[§] Quadratic gain was used in utility weight function 2.

^{||} Nominal gain was used in utility weight function 3.

[¶] Linear income was used in utility weight functions 1 and 2.

Nominal income was used in utility weight function 3.

GAIN shows a similar pattern in all utility functions. For example, utility function 1 will increase by 0.0758 (standard error [SE] 0.0039) for each unit increase in GAIN to the low-income group. The GAIN effects remained statistically significant at the 5% level when the quadratic term GAIN² was added (0.0755; SE 0.0039 in utility function 2). There is a general GAIN trend observed in utility function 3 that sees increases in preference for the low-income group as the number of years increases, starting at −0.6585 (SE 0.0478) for −9 years, increasing to 0.5648 (SE 0.0556) for +9 years.

Personal income is significant in all three models. There is an adverse dose-response association between personal income, both as an ordinal categorical factor (utility functions 1 and 2) and a nominal four-level factor (utility function 3), with participants' tendency to choose the program benefiting the low-income group. It is evident that the negative beta coefficients for personal income levels in Table 4 decrease from 0 in the lowest personal income level to −0.4 in the highest personal income level, indicating that as personal income increases, participants are less likely to choose the program benefiting the low-income group. This is also evident from negative beta coefficients for linear personal income models (utility functions 1 [−0.1407; SE 0.0365] and 2 [−0.1405; SE 0.0364]).

Sex, age, and education level of participants were not significant in utility functions 1 and 2, but models with age, sex, and

education level had better fit compared with models that excluded these factors (Wald $\chi^2 = 529.74$; df 31; $P = 0.03$). Therefore, they were included in further analyses. Two-way interactions were tested for all models and none was significant.

For the calculation of the weights, the three utility functions in Table 4 were investigated: linear, quadratic, and nominal utility functions that do not assume any parametric trend for utility weights. To compare the models' fit, AIC and BIC were used. There was a significant difference between utility function 1 (linear) and utility function 2 (nonlinear) ($P = 0.001$), and according to AIC and BIC values the nonlinear model had better fit. There were also significant differences between utility function 2 and utility function 3 (nominal factors) ($P < 0.0001$); in addition, AIC and BIC for the nominal model had the smallest values between the three candidate models. This means the nominal utility function (utility function 3) has better model performance compared with the linear and quadratic utility functions. Therefore, utility function 3 is the preferred choice for the calculation of the weights.

The equity weights based on utility function 3 were derived by taking the exponential of the coefficients obtained from the RE probit of the gains for utility function 3 (Table 5). GAIN = 0 is the reference category with a weight of 1. The weights represent the chance of the low-income group receiving the gain as the level of GAIN changes. The weights ranged from 0.52 (95% confidence

Table 5 – Equity weights derived from utility function 3 for the low-income group.

GAIN* (y)	Equity weight (95% CI)
–9	0.52 (0.47–0.57)
–5	0.53 (0.49–0.58)
–3	0.75 (0.69–0.81)
–2	0.65 (0.60–0.70)
0	1.00
2	1.27 (1.19–1.36)
3	1.25 (1.16–1.34)
5	1.52 (1.40–1.66)
9	1.76 (1.58–1.96)

CI, confidence interval; LE, life expectancy.

* GAIN indicates gain in LE to the low-income group. For example, –9 indicates a 9-y gain to the high-income group.

interval 0.47–0.57) to 1.76 (95% confidence interval 1.58–1.96), with a tendency for increasing weights as the GAIN to the low-income group increased. Utility function 3 used for the calculation of the weights does not assume any trend for GAIN. This explains why the weight of 0.75 for –3 GAIN is larger than the weight of 0.65 for –2 GAIN.

Equity weights for the positive gains in LE for the low-income group (i.e., 1.25–1.76) could be applied in practice, by weighting QALY gains in the most disadvantaged group. For example, for an intervention targeted to a low SEP group, applying a weight of 1.52 to 20,000 QALYs gained would increase the amount of QALYs to 30,400. The weights less than 1 are not intended for practical use. The weights are intended to be applied to increase the health gains of disadvantaged groups; a requirement therefore is that they be greater than 1.

Discussion

In our study the equity weights derived for health gains to the lowest SEP group ranged from 1.3 to 1.8 when stated preferences were used and from 1.2 to 1.5 when epidemiological data were used. The DCE in this study has demonstrated that people are willing to make trade-offs between efficiency and equity and that health gains are valued differently, depending on which SEP group receives the gain. Simple maximization of total health was shown not to be the basis on which most people make health resource allocation decisions, supporting the results of previous studies [10,21,25–30]. The weights from all-cause mortality and burden of disease data resulted in very similar weights when the same reference groups were used, thus supporting the consistency of the weights. The epidemiological weights for Q1/Q5 using all-cause mortality, burden of disease, and the corresponding preference-based weight for the gain in LE of 5 years are very similar at 1.46, 1.54, and 1.52, respectively.

Our weights are not directly comparable with the weights of Norman et al. [10], because theirs covered other dimensions of the hypothetical group, in addition to income level. This is the first study, to our knowledge, to derive preference-based equity weights for SEP that could be applied in practice. People's preferences have been the conventional method for valuing equity weights, and we also believe this to be the first study to use epidemiological data to calculate weights for a disadvantaged SEP group. Equity weighting of health gains to disadvantaged groups is useful when there is a trade-off between improving total health and health equity. The weights derived could be used to aid decision makers and stakeholders to explore alternative

value judgments around equity. If a program is cost-ineffective yet improves equity, the weights could help decision makers decide the level of concern for equity required for the program to be considered value for money. For example, applying an equity weight of 1.5 to an incremental cost-effectiveness ratio of \$75,000/QALY decreases it to \$50,000/QALY.

We used two different measures of SEP in the two approaches to equity weighting. This was necessary because of the epidemiological data being available only by SEIFA and not by income. It is common for health surveillance surveys to lack SEP data at the individual level. Area-based socioeconomic measures may omit substantial proportions of individual variation in education and income [31], but there is evidence that area-based measures capture the complex relationship between various economic and social phenomena that cannot be picked up by individual-based measures [32]. Income was used as the SEP indicator in the stated preferences approach to facilitate ease of understanding. Ideally, the comparison of the two approaches would be more appropriate if we had used the same measure of SEP for both approaches.

The choice of which approach to use to derive the weight would depend on the preferences of stakeholders and policy-makers. The epidemiological approach would be more suitable when resources for decision makers are limited and a DCE is unlikely to occur. In the epidemiological approach, two weights were calculated—one that compares the lowest quintile with the population average (A) and the other that compares the lowest quintile with the highest quintile (B). Each approach might be considered more preferable in different policy contexts. For example, A would be informative if the objective is to reduce average health loss differences but maintain the current social gradient, whereas B would be most appropriate when the policy objective is to reduce inequalities. Both sets of weights could be used in sensitivity analyses and considered as alternative equity parameters. Similarly, a low and a high weight could be used if preference-based weights are used. Equity weighting analysis does not have to be used as an algorithm for resource allocation decisions [28]. Rather, it is recommended that it be used as a tool to aid decision making. Using different weights in sensitivity analysis would allow the exploration of alternative value judgments around equity [28].

We acknowledge some limitations in the design of the DCE. The choice sets were based on a format used by Dolan and Tsuchiya [21], with LEs that remain fixed. This was of interest to us because it reflects the inherent differences in LE between the income groups. We therefore did not include all possible combinations of LE in the choice sets, but we considered the subset chosen to be adequate for the range of difference in years desired. In doing so we aimed to increase the engagement with participants. In addition, prospect theory states that losses and gains are valued differently [33] and it is possible that posing the questions as gains in LE rather than as losses could have resulted in framing effects. It is also possible that simplifying heuristics may have contributed noise to our data [34]. The “take the best” heuristic may have led to people choosing the group with the most health gains. Nevertheless, this health maximization approach was not chosen by most respondents.

We used an online panel company for the recruitment of participants, and it is arguable that online panel participation is correlated with certain undetectable characteristics. Our sample was over-represented in the ages of 36 to 55 years, and with persons with higher education and higher incomes. Although quotas were applied to obtain a target number of respondents in each demographic group, it became apparent that quotas needed to be modified for age to obtain the desired sample size. We did not detect any differences based on education or in the age group that was over-represented. There was, however, a positive

association with GAIN to the high-income group as own income increased, which could be interpreted as higher income groups being biased toward their own income group and the potential for their own gain.

The epidemiological weights method does not have these weaknesses and may therefore be considered a more suitable approach given the equity aim. One of the strengths of the epidemiological weights method was the ease of obtaining the freely available data. The epidemiological weights were consistent with the preference weights, indicating that people may well find the epidemiological weights approach acceptable. Nevertheless, even if it was coincidental that the preference-based weights are similar in magnitude to the epidemiological weights, it could be argued from a decision maker's perspective that calculating weights using unbiased epidemiological data would enable policymakers to reduce health inequity in an ethical manner. Further research could be undertaken to see which weights are more acceptable to policymakers and to the public.

There are measures of SEP similar to the SEIFA Index of Relative Socio-Economic Disadvantage in other countries, enabling replicability of the results in other contexts. For example, in the United Kingdom, the Index of Multiple Deprivation quintiles incorporates measures of deprivation across domains of income, employment, health and disability, education and training, housing and services, living environment, and crime. These indices are also available in South Africa, Northern Island, New Zealand, and Scotland.

Conclusions

Our aim was to derive weights that could be used in the economic analysis of policies and programs in Australia, particularly in contexts in which using the traditional nonweighted QALYs could increase health inequalities between already disadvantaged groups. Application of our equity weights is the next step, and it is hoped that they can be used to aid decision makers and stakeholders faced with difficult trade-offs between equity and cost effectiveness.

Source of financial support: A. Lal, M. Mohebi, R. Carter, and A. Peeters are researchers within a National Health and Medical Research Council, Centre for Research Excellence in Obesity Policy and Food Systems grant (grant no. APP1041020). A. Peeters is also a recipient of a Career Development Fellowship from the National Health and Medical Research Council. No funding bodies had any role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Supplemental Materials

Supplemental material accompanying this article can be found in the online version as a hyperlink at <http://dx.doi.org/10.1016/j.jval.2018.07.006> or, if a hard copy of article, at www.valueinhealthjournal.com/issues (select volume, issue, and article).

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