Work-in-Progress

Health Impact Analyses of Non-Health Sector Public Health Interventions: Application to Air Pollution Control Measures

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Abstract

A mathematical framework is proposed for Health Impact Analyses, defined as stochastic cost-effectiveness analyses of non-health sector public health interventions in which only health-related costs and effects are included. Non-health benefits and harms are left to be addressed in complementary analyses. The framework is illustrated using a hypothetical study to determine the 'optimal' standard for exposure to an air pollutant with reference only to health considerations . The framework integrates mathematical models, which evaluate the health-related effects and the health-related costs associated with implementing different standards, with mathematical methods to determine the 'health-optimal' standard.

1. Introduction

Most applications of cost-effectiveness analyses (CEA) in health economics have focussed on the evaluation of health sector interventions such as health care technologies or medical therapies (Briggs, 2000; Fenwick *et al.*, 2001). There is now an increasing need to extend the use of the underlying techniques to Health Impact

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Analysis (HIA), defined as the evaluation of non-health sector public health interventions, e.g. air pollution control measures, waste disposal procedures, by their health-related outcomes and health-related costs in full recognition that other outcomes and effects may be important elements of comprehensive evaluation.

Applications of the underlying techniques to non-healthcare sector interventions, as opposed to healthcare sector ones, involve significant differences both in the type of models required and in the evidence base, as well as obviously in the eventual conclusions that can be drawn from the analysis. In general, HIA requires the integration of a hierarchy of models of different scales and scope, spanning pollutant concentration-response models, population exposure models, population flow models and population health models. On the cost side, HIA integrates models of the direct and indirect primary healthcare costs associated with the intervention measures. The evidence base for HIA may also be very different from that in the healthcare sector: the data cannot be obtained from randomised control trials or even case control studies and must be sought from a wide spectrum of environmental and epidemiological studies.

In summary. the objective of this paper is to outline a mathematical framework for HIA, the aim of which is to generate the health-related components of a full stochastic cost-effectiveness analysis of non-health sector public health interventions. The framework is illustrated using the example of air pollution standards.

2. The conceptual framework

In the air pollution case, the intervention options are alternative standards for air pollutants. Figure 1 shows schematically the proposed framework for HIA whose purpose is to evaluate and compare different intervention options.

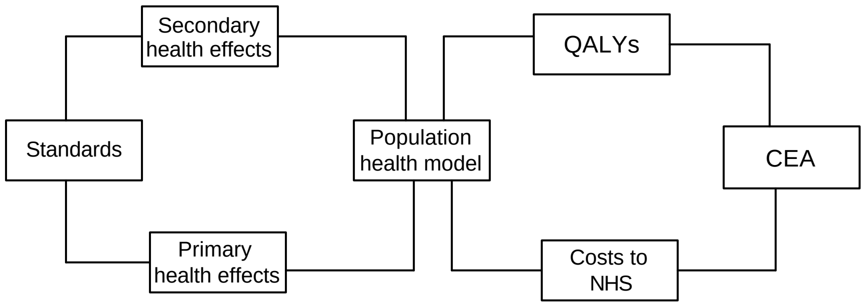

Figure 1: Schematic diagram of the proposed HIA framework in relation to setting air pollution standards.

The above modelling framework sets out the analytical steps towards the determination of the 'health-optimal' standard for an air pollutant. The adoption of any standard has dual effects on health: primary (direct) ones and secondary (indirect) ones. The primary effect is attributed directly to the air pollutant and changes in it by imposition of a standard. For example increasing the standard – or equivalently reducing the concentration – of an air pollutant from its current level is likely to directly improve the health of the exposed population. However, the technology required to achieve the high standard, or the behavioural or other changes prompted by introduction of the standard, could introduce other pollutants, contaminants or non-pollutant-related sources of mortality and morbidity that effect health, perhaps detrimentally. Both the primary and secondary health effects of adopting a standard must therefore be taken into account in the evaluation of the standard.

The output of the population health model is defined in terms of disease states (e.g. cancer, heart attack, and death). The disease states are then mapped into generic health states (e.g. EQ-5D) where each health state has an assigned utility value.

Integrating the years spent in each health state, weighted by their utility value, gives the total Quality Adjusted Life Years (QALYs).

The output of the population health model feeds also into a cost model, which calculates the indirect costs to the NHS of using its resources as the exposed population moves between the different disease states. The outputs of the (health specific) cost-effectiveness module are incremental effects expressed in QALYs and incremental changes in indirect costs, in relation to the effects and costs in the absence of exposure to the air pollutant, but more usefully in relation to other alternative standards including a current one where that is the appropriate comparator.

3. Stochastic cost-effectiveness analyses

Denote by $\{s_i, i = 1..n\}$ the *n* different standards that are to be evaluated. The model simulates for each standard s_i the total net effect $e(s_i, w)$ and the total indirect net cost $c(s_i, w)$ to the NHS of adopting the standard. The functional dependence of e and c on w (which denotes a chance event) reflects model uncertainty.

Cost-effectiveness acceptability curves (CEAC) or frontiers have been used increasingly and effectively in CEA by health economists (Fenwick *et al.*, 2001; Briggs *et al.*, 2002). It is proposed to use CEAC frontiers here because the decision-problem involves multiple interventions (standards) and the net benefits are likely to be skewed.

Denote by l the willingness to pay for an additional unit of effect. The net benefit of adopting standard s_i is

$$b(s_i, w) = l\ e(s_i, w) - c(s_i, w) \qquad (1)$$

For each standard s_i, denote by $r(s_i, l)$ the probability that, conditional on the value of l, the net benefit of adopting standard s_i is higher than that of any other standard s_j

$$r(s_i, l) = P\big(b(s_i, w) > b(s_j, w) \big| l\big) \qquad j \neq i \qquad j = 1...n \tag{2}$$

The CEAC frontier $f(l)$ defines the uppermost bound (also conditional on the value of l) constructed from the probability curves $\{r(s_i, l); i = 1...n\}$

$$f(l) = \max_{\{s_i, i=1..n\}} (r(s_i, l)) \tag{3}$$

The 'optimal' standard s_k for a given value l is given by the decision-analytical rule

$$s_k(l) = Arg\left(\max_{\{s_i, i=1..n\}} (r(s_i, l))\right) \tag{4}$$

Equation (4) defines the optimal standard as that which has the highest probability of having the greatest net benefit.

4. The application

There is considerable epidemiological evidence on the harmful effects of air pollution on health and there is also considerable scientific evidence on possible causal pathways that could explain the physiological mechanisms by which some air pollutants induce harmful effects in humans (Hester and Harrison, 1998; Holgate *et al.*, 1999). The epidemiological evidence on the medical effects of air pollution has been used to set health based air quality standards or guidelines (DoH, 1997; Harrison, 1998; WHO, 2000) and to quantify the indirect costs to society of the negative health effects of air pollution (DoH, 1999). It is argued here that the proposed framework integrates in a more coherent and inclusive manner the evidence base of primary and secondary health effects of air pollution to determine 'health-optimal' standards for air pollutants.

5. The concentration-response relationship

The concentration-response relationships between air pollution and mortality are often described by linear models, piecewise linear models with threshold or non-linear models (Schwarts *et al.*, 2001; Schwarts *et al.*, 2002). Figure 2 below shows schematically some of the commonly established relationships. Line L represents a linear relationship between percentage increase in deaths z at a defined concentration of a pollutant q relative to that at zero (or undetectable) concentration. Lines NL_1 and NL_2 represent non-linear relationships between z and q. Line NL_1 could be polynomial or logistic. Line NL_2 represent a threshold phenomena in which it is assumed that the pollutant has no impact on mortality for concentrations below a threshold value T and then it has a linear effect on mortality with increasing concentrations. Note that the response measure is not always defined in mortality terms but is often defined in morbidity terms. For example, the response in Figure 2 could be the percentage increase in cancer incidence.

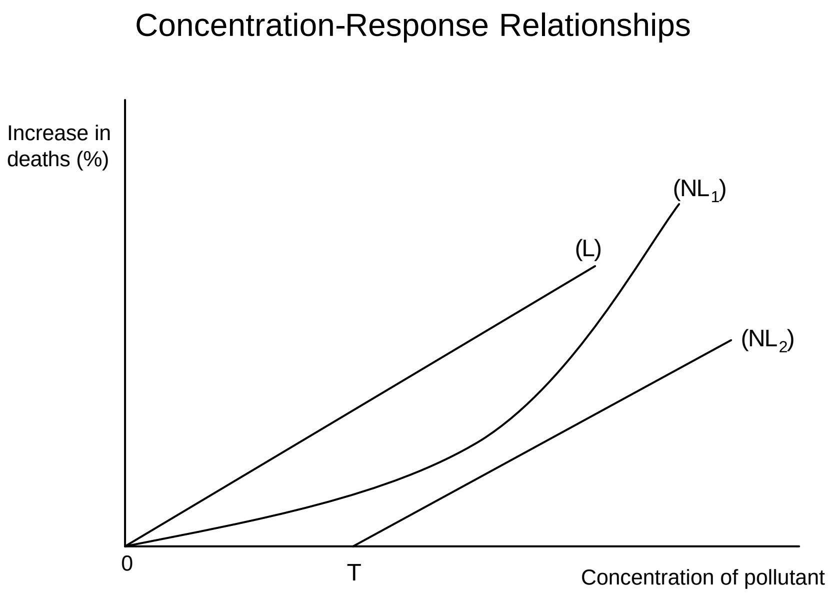

Figure 2. Some of the concentration-response relationships. Line L describes a linear relationship and lines NL_1 and NL_2 describe non-linear relationships.

In the HIA framework, the concentration-response relationship of an air pollutant forms part of the medical evidence that is required to carry out the health-specific CEA. Additional medical evidence is also required on the secondary health effects of adopting higher standards. For CEA, the medical evidence needs to be presented in the form of probabilities of disease states (responses) given the concentration levels of air pollutants.

Concentration-response relationships of the type shown in Figure 2 need therefore to be converted to a form which can be processed in our framework. For illustrative purposes, assume that the concentration-response relationship is of type NL_2. Figure 3 reproduces this relationship and superimposes on it the standards to be evaluated. In this figure, and throughout the paper, the variables q and s are used to denote respectively the concentration of an air pollutant and a standard.

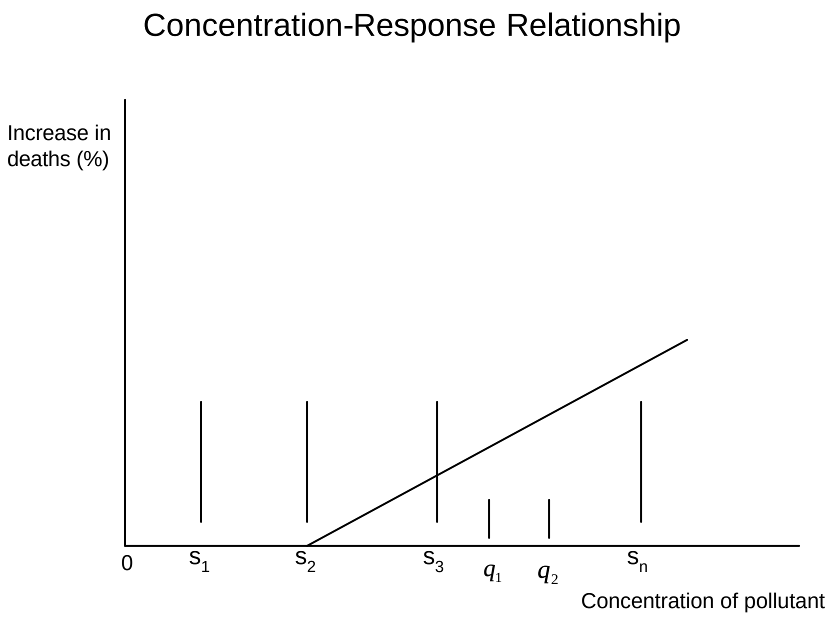

Figure 3. An example of concentration-dose relationship. s_1 to s_n are the *n* standards to be evaluated and q_1 and q_2 are two concentrations of the air pollutant.

An 'optimal' standard is often identified in epidemiological analysis with the 'safest' exposure level as read from the concentration-response relationship. For example in the case of the concentration-response relationship shown in Figure 3, s_2 is deemed to be the 'optimal' standard because it is the highest concentration of the pollutant that results in 'negligible' increase in mortality or morbidity incidence. But this represents a pre-emption of the decision as to the optimal level and HIA rejects any pre-emption based solely on the characteristics of the exposure-response relationship . It also takes a broader view taking into account both primary and secondary health effects and *integrating the health outcomes of different characteristic scales such as disease states, health states and life expectancy measures adjusted for health-related quality of life (i.e. QALYs).*

6. Primary and secondary health effects

Let s_j and s_i be two standards where standard s_j is 'higher' than standard s_i. If standard s_j corresponds to concentration q_j and standard s_i corresponds to concentration q_i, then by definition $q_j < q_i$ (standard s_j is 'higher' than standard s_i).

Consider first standard s_i. Let $p_A(x, q_i)$ be the probability that an individual of age x in a population exposed to concentration q_i of the pollutant will get (non-fatal) disease A over the period of evaluation t. Increasing the standard from s_i to s_j means reducing the pollutant concentration to which the population is exposed from q_i to q_j. The relative risk reduction (a_A) in the incidence rate of disease A obtained by reducing the pollutant concentration from q_i to q_j is

$$a_A = \frac{p_A(x, q_j) - p_A(x, q_i)}{p_A(x, q_i)} \tag{5}$$

Equation (5) does not take into account secondary health effects, or 'downstream' health effects, which can result from technologies that reduce the pollutant concentration to q_j. Assume that the reduction in pollutant concentration can only be achieved by technologies that increases the incidence rate of a (non-fatal) disease B. Or that behavioural changes, such as those prompted by a rising price of products particularly affected by the (change in) standard, have a similar effect.

Let $p_B(x, q_j)$ be the probability that an individual of age x, in a population exposed to technologies which reduce the pollutant concentration to q_j, will get disease B over the period of evaluation t. The relative risk increase (a_B) in the incidence rate of disease B obtained by reducing the pollutant concentration from q_i to q_j is

$$a_B = \frac{p_B(x,q_j) - p_B(x,q_i)}{p_B(x,q_i)} \qquad (6)$$

HIA hence takes into account both primary and secondary health effects in the evaluation of the standards.

7. Models of probability of disease incidence

To complete the space of disease states, add the disease states corresponding to 'death' (*D*) and 'good health' (*H*). Let $p_D(x)$ and $p_H(x)$ be respectively the probability that a person of age *x* dies (occupies disease state *D*) and remains healthy (occupies disease state *H*) over the period of evaluation. In other words,

$$p_A(x,q_i) + p_B(x,q_i) + p_H(x) + p_D(x) = 1 \qquad (7)$$

Logistic regression models are used to describe both $p_A(x,q_i)$ and $p_B(x,q_i)$:

$$\begin{aligned} \log\left(\frac{p_A(x,q_i)}{1 - p_A(x,q_i)}\right) &= g_A(x,q_i) \\ \log\left(\frac{p_B(x,q_i)}{1 - p_B(x,q_i)}\right) &= g_B(x,q_i) \end{aligned} \qquad (8)$$

The *logit* transformation converts the probability measure $p_A(x,q_i)$ (and $p_B(x,q_i)$) to a measure (log odds) between $-\infty$ and $+\infty$. Logistic regressions are commonly used in modelling probabilities or proportions in medical statistics (Bland, 2000). The terms $g_A(x,q_i)$ and $g_B(x,q_i)$ can be linear or nonlinear in q_i.

Note that because of model uncertainty $g_A(x,q_i)$ and $g_B(x,q_i)$ are stochastic, which implies that $p_A(x,q_i)$ and $p_B(x,q_i)$ are also stochastic. In other words, Eqn. (8) becomes

$$\log\left(\frac{p_A(x,q_i,w)}{1-p_A(x,q_i,w)}\right)=g_A(x,q_i,w)$$
$$\log\left(\frac{p_B(x,q_i,w)}{1-p_B(x,q_i,w)}\right)=g_B(x,q_i,w) \quad (9)$$

Monte Carlo simulations are used to generate values for $p_A(x,q_i)$ and $p_B(x,q_i)$ over all ages for the CEA.

8. The optimal standard

Now let u_A and u_B be respectively the utilities assigned to diseases *A* and *B*. Furthermore let $t_A(w)$, $t_B(w)$ and $t_H(w)$ be respectively the duration in years that a person stays in disease state *A*, *B* and *H* over the period of evaluation, i.e.

$$t_A(w)+t_B(w)+t_H(w)\leq t \quad (10)$$

The net change in QALYs per person over period t is given by

$$e(s_i,w)=u_A\ p_A(x,q_i,w)t_A(w)+u_B\ p_B(x,q_i,w)t_B(w)+\ p_H(x)t_H(w) \quad (11)$$

where u_A and u_B are the utility values assigned to the disease states.

The net indirect costs to the NHS are those incurred due to primary healthcare and hospitalisation associated with each disease state. If a person in disease state *A* incurs costs of £ $s_A(w)$ per unit time and a person in disease state *B* incurs £ $s_B(w)$, then the total indirect costs is

$$c_i(w)=s_A(w)t_A(w)\,p_A(x,q_i,w)+s_A(w)t_A(w)\,p_A(x,q_i,w) \quad (12)$$

The net benefit of adopting standard s_i is therefore given by

$$b(s_i, w) = l\ e(s_i, w) - c(s_i, w) \qquad (13)$$

The optimal standard is obtained through the procedure outlined in Section 3.

9. Conclusion

Determining optimal standards for air pollution exposure with reference only to health consideration is one exemplar function of Health Impact Analysis. The mathematical framework for HIA uses stochastic cost-effectiveness analysis methods to determine the health-optimal standard for exposure. Clearly, health impact analysis constitutes only one element of a full and comprehensive evaluation of such interventions, which requires non-health considerations to be taken into a count. The case for this partial exercise lies both on its own value and in the way it will hopefully prompt equivalently serious and analytical CE-Impact Analyses of those other aspects, be they environmental, economic or whatever.

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Note to HESG Participants

This papers introduces the basic ideas underpinning our approach to HIA. Our next step will be to illustrate the framework with a numerical example which describes a more complex application than is described in this paper. However, we would value at this stage any comments and criticisms you may have on our general approach.