Evaluation of the Cold Weather Plan for England: Modelling of Cost-Effectiveness

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SUPPLEMENTARY MATERIAL

Methods

Health impact assumptions

In order to integrate all the health benefits (i.e. associated with premature deaths, hospital admissions avoided, and community contacts) into a single measure of QALY, a number of assumptions have been made:

1. We used quality of life (QoL) adjustment figures for COPD. Borg et al [1] gave mean QoL (q) weights for four COPD categories of increasing severity without exacerbations as 0.8971, 0.7551, 0.7481 and 0.5843 respectively, and for three exacerbation severity categories as q×0.95 (mild), q×0.85 (moderate) and q×0.30 (severe). Assuming equal prevalence in COPD categories without exacerbations and equal prevalence in the three exacerbation categories, we averaged QoL weights over the four COPD severity categories without exacerbation ($\bar{q}$=0.7462), and assumed that only COPD patients with exacerbations would lead to hospital admissions or deaths.

2. For mortality, we have assumed that most cold-related deaths occur in the elderly and this is supported by the epidemiological analysis carried out on deaths occurring in England between 1st January 1993 and 31st December 2006, which showed that the percentage change in the daily average number of deaths in winter relative to the daily average over the year is 1.77%, 2.49%, 4.34% and 4.96% for the age groups 0-64 years, 65-74 years, 75-84 years and 85+ years, respectively [2]. The highest winter-related mortality rate is among people aged 75+ years.
3. We used life tables to estimate the population weighted average life expectancy of people aged 75+ years. The estimated average life expectancy is 8.4 years. If m deaths are averted, this is equivalent to $8.4\ m$ Life Years (LYs) gained. The estimate of LYs gained is an approximation, because life expectancy is a population average measure, whereas premature cold-related deaths are more likely to occur in those with pre-existing conditions (such as COPD), with lower life expectancy.
4. To obtain an estimate of QALYs gained due to deaths averted, we multiplied the average LYs gained by the average QoL for COPD patients with exacerbations, i.e. $8.4 \times 0.7462 \times \left(\frac{0.95+0.85+0.3}{3}\right) = 4.39$. In other words, every m deaths averted equates to $m \times 4.39$ QALYs gained.
5. For hospital admissions, we also assumed that only COPD patients with exacerbations would be admitted to hospital. We also assumed that the QoL gain associated with a hospital admission avoided would last for 1 year. This means that if n hospital admissions are avoided, the QALYs gained is $n \times .7462 \times \left(1 - \left(\frac{0.95+0.85+0.3}{3}\right)\right) = n \times 0.224$ QALYs gained.

6. We assumed that community contacts would avert some COPD patients from having exacerbations and that the QoL gained would last for one year. As in the case of hospital admissions avoided, this means that $s \times .7462 \times \left(1 - \left(\frac{0.95+0.85+0.3}{3}\right)\right) \times \frac{1}{365} = s \times 0.224 \times \frac{1}{365}$ QALYs gained per day for every s additional contacts made with COPD patients.
7. We used data from an evaluation of the Healthy Outlook® COPD health forecasting alert service to provide guidance on the likely number of additional community contacts per patient, by comparing pre- and post- weather-based alert services over the winter period (Table S1) [3]. The only statistically significant change found in health care utilisation over the winter period was that associated with home visits by general practice staff ($p<0.001$). We have assumed that the same pool of patients is visited post-CWP as pre-CWP, and that the number of contacts per patient increases by $\frac{(0.92-0.05)}{5\times30}$ per day (the division by 5×30 is to convert the total number of extra contacts to a daily rate over the 5 month winter period). There are about 900,000 COPD diagnosed patients in the UK. If we assume that a proportion θ of patients (or clients) are visited pre-CWP, then the contacts increase to $\theta \times 9 \times 10^5 \times \frac{(0.92-0.05)}{5\times30}$ post-CWP and results in $\theta \times 9 \times 10^5 \times \frac{(0.92-0.05)}{5\times30} \times 0.224 \times \frac{1}{365}$ QALYs gained. To calculate total QALYs, multiply by the number of days over the time horizon of interest.

Health impact calculation

Figure S1 shows the temperature-mortality relationship during winter which is used in the health impact calculations. Below a threshold temperature value τ_d the mortality relative risk (RR_d) increases linearly with decreasing temperatures. A similar relationship holds for the relative risk of hospital admissions but with a different threshold temperature τ_h(not shown in Figure S1)

Calculation of health benefits associated with deaths and hospital admissions

Denote by θ_d the increment in RR_d per degree (i.e. the slope of line L in Figure S1). The number of premature cold-related deaths d for any day for which the daily temperature $|T|$ is below the threshold (i.e. $|T| > |\tau_d|$) is given by:

$$d = d_0 \left(\frac{(1+\theta_d)^{|T-\tau_d|} - 1}{(1+\theta_d)^{|T-\tau_d|}} \right) \tag{1}$$

where d_0 is the baseline number of daily winter deaths. The counterpart equation for hospital admissions is:

$$h = h_0 \left(\frac{(1+\theta_h)^{|T-\tau_h|} - 1}{(1+\theta_h)^{|T-\tau_h|}} \right) \tag{2}$$

where h is the number of premature cold-related daily hospital admissions, h_0 is the baseline number of daily hospital admissions over winter, and τ_h is the threshold for hospital admissions.

Equations (1) and (2) are used to determine the pre-CWP health burden. The sum of the health benefits is:

$$\Delta b = \delta\,\zeta\left(d_0\left(\frac{(1+\theta_d)^{|T-\tau|}-1}{(1+\theta_d)^{|T-\tau|}}\right)f_1 + h_0\left(\frac{(1+\theta_h)^{|T-\tau|}-1}{(1+\theta_h)^{|T-\tau|}}\right)f_2\right) \qquad (3)$$

where the constants δ and ζ are respectively the effectiveness of the plan if fully implemented and the degree of implementation of the plan, and the constants f_1 and f_2 are respectively the conversion constants from counts of deaths and hospital admissions to QALYs.

Equation (3) gives the health benefit per day. If we donate by subscript T_i the temperature on day i, then the health benefits accrued over Ω years (ΔB) ar given by:

$$\Delta B = \sum_{i=1}^{365\,\Omega}\delta\,\zeta\left(d_0\left(\frac{(1+\theta_d)^{|T_i-\tau_d|}-1}{(1+\theta_d)^{|T_i-\tau_d|}}\right)f_1 + h_0\left(\frac{(1+\theta_h)^{|T_i-\tau_h|}-1}{(1+\theta_h)^{|T_i-\tau_h|}}\right)f_2\right) \qquad (4)$$

Costs

Relevant primary, social and community care costs, and hospital admission costs for 2012 were taken from PPSRU [4]. Table S2 lists professional staff likely to contact patients/clients in the community (according to the CWP) and their corresponding costs (which depend on the nature of the contact). In the absence of evidence on the nature of contacts with patients/clients in the community, we have assumed that each additional contact will incur a cost drawn randomly from a log-normal distribution informed by Table S2 with mean £51, median £49 and 10^{th}-90^{th} percentile range £36-£68.

The same approach is used for estimating the unit cost of a hospital admission. Table S3 shows the cost of different broad types of hospital admission and visits to A&E [4]. Again, in the absence of any ‘hard data’, we have assumed that each hospital admission avoided would save a cost drawn from a log-normal distribution *informed* by Table C3, with mean £556, median £403, and 10^{th}- 90^{th} percentile range £145-£1125.

The total cost over Ω years is given by:

$$\Delta C = \sum_{i=1}^{365\times\Omega} \delta\, \zeta \left(\beta\, u_i - \alpha\, h_0 \left(\frac{(1+\theta_h)^{|T_i-\tau_h|} - 1}{(1+\theta_h)^{|T_i-\tau_h|}} \right) \right) \tag{5}$$

where α and β are respectively the unit costs of hospital admission and primary/social care contact and u_i is the additional number of contacts on day i; the remaining terms of equation (5) are described above.

Selection of temperature time series

There are several alternative sources of daily temperature time series which could have been used to drive the model. These include the use of stochastic weather generators to simulate daily temperature in England under different climate scenarios [5,6]. However the publically available daily weather generators are not-physics based and are originally derived from fitting empirical models to rainfall data from which temperature and other weather variables were determined. These were primarily used for agriculture and are not well suited to simulate extreme events. Although some were adapted to simulate extreme weather events, they focussed on extreme hot temperatures and rain fall, and were not tested for cold extremes [7]. For these reasons, we opted to use historical temperature data for the simulations.

Fitting extreme value probability distribution to CET data

There have been some investigations of the extremes of CET using extreme value theory [8,9]. Extreme value theory is used to characterise the probability distribution of extreme events [10]. The extreme value theorem states that the minimum (or maximum) of independent identically distributed random variables converges asymptotically to one of three types of a distribution known as the Generalized Extreme Value distribution irrespective of the probability density function of the parent random variable [11].

We analysed the minima of daily CET by fitting a generalized minimum extreme value distribution with location parameter μ, scale parameter σ and shape parameter ξ and of probability density function:

$$\emptyset(T) = \frac{exp\left(-\left(1+\frac{(\mu-T)\,\xi}{\sigma}\right)^{-\frac{1}{\xi}}\right)\times\left(1+\frac{(\mu-T)\,\xi}{\sigma}\right)^{-1-\frac{1}{\xi}}}{\sigma} \qquad (6)$$

to the daily minima of the CET time series record using maximum likelihood estimation [11]. Figure S2 shows the estimated probability density function (PDF) fitted by maximum likelihood estimating alongside the empirical histogram. The PDF at a particular value gives the relative likelihood that the minimum temperature takes that value and the total area underneath the PDF is unity. Figure S3 gives the estimated cumulative distribution function (CDF) of the daily minimum temperature. The CDF at a particular value gives the probability that the minimum temperature is less than or equal to that value. Based on the estimated

GEV distribution, we simulated a minimum daily temperature time series over the specified time horizon. Figure S4 shows the histogram of the simulated temperature series along with the continuous PDF.

Overall simulation model

The overall simulation model is summarised by the steps below:

1. Initialise the key parameters of the CWP. These are:
   1.1. the upper bound of the effectiveness of the CWP (if fully implemented)
   1.2. the average degree of implementation of the CWP
   1.3. the size of the vulnerable population (patients/clients) which can be contacted in the community
   1.4. the proportion of the vulnerable population contacted pre-CWP
   1.5. time horizon for analysis
2. Fit a generalized extreme value (GEV) distribution to the daily minimum CET time series over 100 years.
3. For each day:
   3.1. Draw randomly a minimum temperature from the GEV distribution.
   3.2. Calculate the incremental number of deaths and hospital admissions.
   3.3. Calculate the daily additional number of contacts with patients/clients in the community.
   3.4. Draw randomly the unit cost of contact and multiply it by the number of contacts to calculate the daily cost of community contact with patients/clients.
   3.5. Draw randomly the unit hospital admission cost and multiply it by the number of hospital admissions to calculate the daily hospital admissions savings.
4. Convert each of the health gains to QALYS and sum them over the time horizon.
5. Sum the daily cost of community contacts over the time horizon.
6. Sum the daily savings associated with hospital admissions avoided.
7. Subtract the savings from the contact cost to calculate the overall cos.t
8. Calculate the cost-effectiveness ratio.

References

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Table S1: Number of contacts with COPD patients.

Type of contact	Number per patient (pre-COPD alert service)	Number per patient (post-COPD alert service)
Telephone consultations by general practice	0.019	0.031
Home visits by general practice	0.05	0.92**
Home visits by COPD ESD[+] team	0.09	0.26

Data based on Bakerly *et al* 2011.

[+]COPD Early Support Discharge team.

** Statistically significant at $p<0.001$

Table S2: Unit costs for professional staff who make contact with patients/clients in the community.

Profession	Cost of contact (£) per patient/client per hour*
Community nurse	42 to 61
Nurse (mental health)	35 to 67
Health visitor	43 to 63
Nurse specialist (community)	43
Nurse GP practice	35 to 45
Social worker**	39 to 54
Social worker assistant	28
GP consultation ***	43 to 110

*The range depends on the nature of the contact.

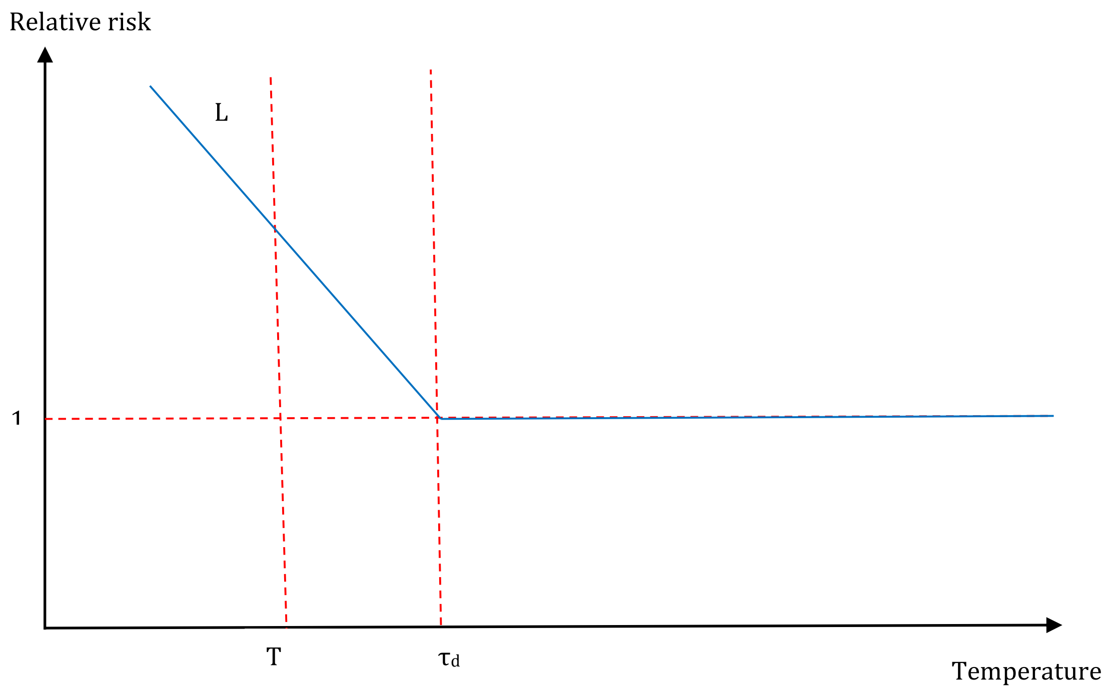
**The upper range of the unit cost for social worker (£156 per hour) has been excluded.

*** The GP consultation cost is *per session* (and also depends on the nature of the contact).

Table S3: Unit costs of relevant hospital admissions.

Type of admission	National average (£)	Lower quartile (£)	Upper quartile (£)
Non-elective inpatient long stays	2,461	1,771	2,865
Non-elective inpatient short stays	586	386	688
A&E treatments leading to admissions	146	114	171
A&E treatments leading to no admissions	112	93	130

Figure S1: The temperature-mortality relationship.



τ_d is the epidemiological threshold and T is the temperature on a particular day

Figure S2: Fitted Generalized Extreme Value (GEV) distribution and the empirical histogram

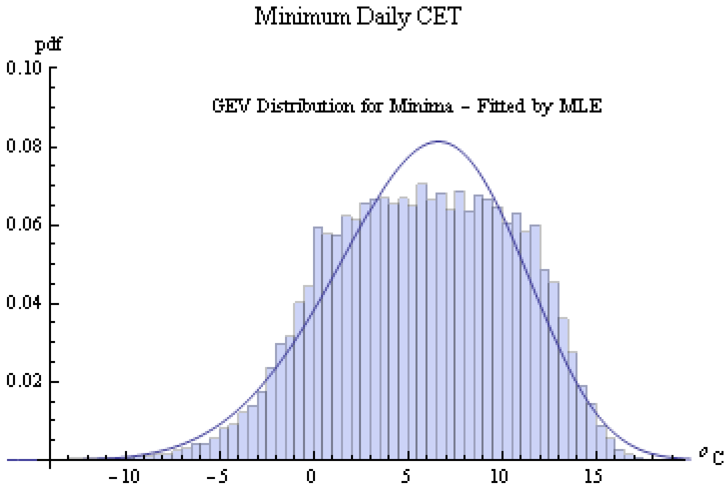


Figure S3: Cumulative distribution function (CDF) of the simulated temperature.

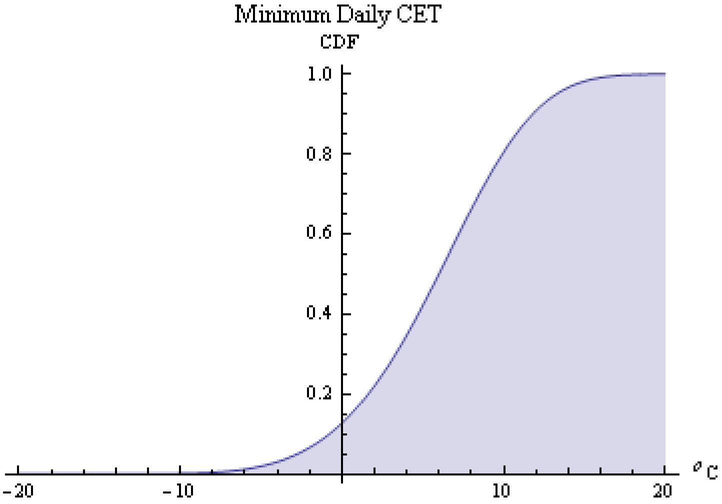


Figure S4: Histogram of the simulated minimum temperature over the time horizon and the continuous PDF