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An analysis of the potential impact of various ozone regulatory standards on mortality†

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Abstract

Ground-level ozone, an air pollutant that is monitored by the Environmental Protection Agency (EPA), damages human health by irritating the respiratory system, reducing lung function, damaging lung cells, and aggravating asthma and other chronic conditions. In March 2008, the EPA strengthened ozone standards by lowering acceptable limits from 84 parts per billion to 75 parts per billion. Here epidemiologic data is used to study the effects of ozone regulation on human health and assessed how various regulatory standards for ozone may affect nonaccidental mortality, including respiratory-related deaths during ozone season. The assessment uses statistical methods based on hierarchical Bayesian models to predict the potential effects of the different regulatory standards. It also analyzes the variability of the results and how they are impacted by different modeling assumptions. We focused on the technical and statistical approach to assessing relationship between new ozone regulations and mortality while other researches have detailed the relationship between ozone and human mortality. We shows a statistical correlation between ozone regulations and mortality, with lower limits of acceptable ozone linked to a decrease in deaths, and projects that mortality is expected to decrease by reducing ozone regulatory standards.

Keywords: Hierarchical model, mortality, ozone regulatory standard, rollback.

1. Introduction

Ozone is not emitted directly by car engines, but rather is formed in the atmosphere when nitrogen oxides and volatile organic compounds react in the presence of sunlight. Thousands of sources contribute to ground-level ozone, including motor vehicle exhaust and chemical solvents. Exposure to tropospheric ozone has been widespread and linked to adverse health effects, including increased rates of hospital admissions and emergency department visits, exacerbation of chronic respiratory conditions (e.g., asthma), and decreased lung function. Recent researches have linked short-term ozone exposure to premature mortality, but the exposure response curve for ozone remains inconclusive. Interpretation of this evidence is

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constrained by the limited range of locations included in these reports, the variability of methods used, and the imprecision of estimates from some of the studies (e.g., see Lee, 2008).

The relation between ozone and health is complicated by the complex, nonlinear chemical formation of tropospheric ozone, which is temperature driven, with higher ozone levels at higher temperatures. In 1997, the US Environmental Protection Agency (EPA) proposed revisions to the National Ambient Air Quality Standard (NAAQS) for ozone, adding a daily maximum 8-hour standard of 80 ppb (parts per billion by volume) while phasing out the daily hourly maximum standard of 120 ppb. U.S. EPA regulations specify that values between 80 and 84 ppb can be rounded down and are not considered exceedances (U.S. EPA 1997). These changes were prompted by evidence from epidemiologic, controlled human exposure, and toxicologic studies that identified adverse health effects at ozone concentrations below the existing 1-hour NAAQS. Many areas in the United States exceed the current health-based U.S. National Ambient Air Quality Standard (NAAQS) for ozone (U.S. EPA 2004). Elevated concentrations of ozone are also a growing concern for rapidly developing nations with rising emissions of ozone precursors from expanding transportation networks. Because of the relevance of epidemiologic evidence to the NAAQS for ozone and other pollutants, updated and expanded time-series studies of ozone are informative to the regulatory process.

In March of 2008, EPA promulgated a reduction in the current ozone regulation standard from 84 ppb to 75 ppb based on the air quality indicator (the 4th largest daily maximum 8-hour ozone). The Agency expects designations based on 2006-2008 air quality data will take effect in 2010 for the 2007 8-hour ozone standard. Bell *et al.* (2004, 2006) were critical in the EPAs scientific reviews. As the current NAAQS is reexamined, there are several critical questions about association of ozone exposure and mortality: Can ozone affect mortality even at low levels? Are current regulations sufficiently stringent to prevent mortality? Is there an attainable threshold ozone level that does not affect mortality?

To assess the effect of new ozone regulation on mortality corresponding to EPA proposal to strengthen the air quality standards for ground-level ozone, we used statistical analysis and databases developed for the National Morbidity, Mortality, and Air Pollution Study (NMMAPS), a large multi-city air pollution study based at Johns Hopkins since 1997. NMMAPS database (2004) including 108 large US urban areas for 1987-2000, to perform a multisite time-series study of ozone and mortality together with data on meteorology (temperature, dewpoint, etc.) and air pollution (O_3, PM_{10}, SO_2, NO_2, CO). In addition, a current observed ozone process needs to be adjusted to satisfy new ozone regulatory standard. To generate adjusted ozone process, we consider rollback functions, air quality adjustment procedures in ozone exposure models by EPA (Johnson, 2002). In past applications of various exposure models to particular study areas, input air quality data sets has been typically developed under the baseline conditions and conditions in which the area just attains a specific NAAQS. Baseline conditions are usually represented by unadjusted air quality data reported by fixed-site monitors in the area during a recent calendar year. Attainment conditions are simulated by applying an air quality adjustment procedure to the baseline data.

Based on adjusted ozone process, we estimated the effect of the proposed ozone standard regulatory on the national average relative rate of mortality associated with short-term exposure to ambient ozone for 95 large US urban communities from 1987-2000. We used distributed-lag models for estimating community-specific relative rates of mortality adjusted for time-varying confounders (weather, seasonality, and long-term trends) and hierarchical models for combining relative rates across communities to estimate a national average relative rate, taking into account spatial heterogeneity. These results indicate a statistically significant association between ozone regulations and mortality on average for 95 large US urban communities, which include about 40% of the total US population. The findings indicate that this widespread pollutant adversely affects public health.

2. Statistical analysis

2.1. Statistical modeling

We first consider generalized linear model based on overdispersed Poisson model for mortality (see McCullagh and Nelder, 1989; Bell *et al.*, 2006). For $t = 1, \ldots, T$ and $c = 1, \ldots, C$, our data are the number of daily nonaccidental deaths for community c on day t, denoted by Y_t^c. Suppose the data model is based on Poisson process with intensity function μ_t^c. That is,

$$Y_t^c \sim Poisson(\mu_t^c) \text{ with } Var(Y_t^c) = \phi_c \mu_t^c, \tag{2.1}$$

where the parameter ϕ_c explains overdispersion of community c. The uncertainties of overdispersed Poisson model are all assumed to be mutually independent through time. The Poisson intensities μ_t^c in (2.1), can be expressed in terms of ozone (with different lags), weather, seasonality, long-term trends, and copollutants for three age groups (< 65, $65 - 74$, and ≥ 75 year). Smooth functions of calendar time (natural cubic splines) were used to adjust for seasonality and longterm trends, such as influenza epidemics. Interaction terms between smooth functions of time and agespecific indicators (< 65, $65 - 74$, ≥ 75 years) are also added to further adjust for seasonal mortality patterns that could vary by age group. The potential confounding effect of weather is controlled by including smooth functions of temperature, the average of the 3 previous days' temperature, dew point, and the average of the 3 previous days' dew points. That is,

$$\begin{aligned}\log \mu_t^c = {} & \beta^c x_t^c + \alpha^c DOW_t + \boldsymbol{\gamma}_1^c ns(time, 7/year) + \boldsymbol{\gamma}_2^c ns(T_t^c, 6) \\ & + \boldsymbol{\gamma}_3^c ns(T_{t-1,t-3}^c, 6) + \boldsymbol{\gamma}_4^c ns(D_t^c, 3) + \boldsymbol{\gamma}_5^c ns(D_{t-1,t-3}^c, 3) \\ & + \text{interaction terms for age and time,}\end{aligned}$$

where

- μ_t^c is the expected number of deaths for community c on day t.
- x_t^c is the average of the same and previous days' daily O_3 concentrations in community c on day t.
- DOW_t is the categorical variable for day of the week on day t.
- $ns(time, 7/year)$ is the natural cubic spline function of calendar time with 7 degree of freedom per year.
- $ns(T_t^c, 6)$ is the natural cubic spline function for temperature with 6 degree of freedom.
- $ns(T_{t-1,t-3}^c, 6)$ is the natural cubic spline function of the average of the 3 previous days' temperature with 6 degree of freedom (adjusted for current day temperature).

- $ns(D_t^c, 3)$ is the natural cubic spline function for dew point with 3 degree of freedom.
- $ns(D_{t-1,t-3}^c, 3)$ is the natural cubic spline function of the average of the 3 previous days' dew points with 3 degree of freedom (adjusted for current day dew point).
- interaction terms for age and time are the interaction terms between natural cubic spline function of time and age specification indicators (< 65, $65-74$, and ≥ 75 year).

Since ozone concentrations are typically available daily, we can consider constrained distributed-lag (CDL) model and unconstrained distributed-lag (UDL) model to estimate community-specific relative rates of mortality associated with exposure to ozone levels during several previous days, which allowing more flexibility for exploring the lag between exposure and death than single-lag models (see Bell *et al.* 2004). For example,

$$\underbrace{\boldsymbol{\beta}^c \mathbf{x}_t^c = \beta_0^c x_t + \beta_1^c \bar{x}_{t:t-3}^c + \beta_2^c \bar{x}_{t:t-6}^c}_{CDL} \text{ or } \underbrace{\boldsymbol{\beta}^c \mathbf{x}_t^c = \sum_{j=0}^{6} \beta_j^c x_{t-j}^c}_{UDL}.$$

At the second stage, hierarchical model is adopted to combine the relative rate estimates obtained from the community-specific distributed-lag models to produce a national average estimate of the asociation between ozone and mortality that accounts for within-community and across-community variability. With this 2-stage model, variation across communities in the short term effects of ozone can be explored and an effect estimated for the nation in (2.2) and (2.3). The effect of O_3 on mortality for each community c is modeled of the form

$$\hat{\boldsymbol{\beta}}^c | \boldsymbol{\beta}^c, \hat{\Sigma}^c \sim MVN(\boldsymbol{\beta}^c, \hat{\Sigma}^c), \tag{2.2}$$

where $\hat{\boldsymbol{\beta}}^c$ is an estimate of the true community-specific relative rate, $\boldsymbol{\beta}^c$, and $\hat{\Sigma}^c$ is the corresponding estimated covariance matrix. The prior for $\boldsymbol{\beta}^c$ is

$$\boldsymbol{\beta}^c | \boldsymbol{\mu}, \Omega \sim MVN(\boldsymbol{\mu}, \Omega), \tag{2.3}$$

where $\boldsymbol{\mu}$ is the true national average relative rate and Ω is the covariance matrix of the true community-specific relative rates, $\boldsymbol{\beta}^c$.

Bell *et al.* (2004) discussed several sensitivity issues related to the modeling: (1) inclusion of co-pollutant such as PM_{10} as a potential confounder, (2) exclusion of days with high temperatures to control for the potential confounding effect of heat waves; (3) specication of the degrees of freedom in the smooth functions of time to control for seasonality and long-term trends, and (4) use of different ozone exposure metrics: daily average, 8-hour maximum, and 1-hour maximum.

2.2. Rollback adjustment

EPA proposed to strengthen the air quality standards for ground-level ozone in 2007. The Agency expects designations based on 2006-2008 air quality data will take effect in 2010 for the 2007 8-hour ozone standard. The current observed ozone process needs to be adjusted to satisfy new ozone regulation to assess the effect of new ozone regulation on mortality. In order to adjust the current observed ozone process to satisfy new ozone regulatory standard, we adopt the rollback transformation (Johnson, 2002). Various exposure models are applied to air quality data sets for the study area that represent baseline conditions and attainment conditions. While baseline conditions are usually represented by unadjusted air quality data reported by fixed-site monitors in the area during a recent calendar year, attainment conditions are simulated by applying an air quality adjustment procedure (AQAP) to the baseline data. In our problem, baseline condition is current ozone process and attainment condition is ozone process under the new ozone regulatory standard. Rollback function attempts to "predict" how a given ozone series would change under a new regulation scenario, and it is needed to investigate health effects. Original approach is modified for current ozone series to satisfy new regulation standard based on current AQI. As many of the early methods have been superseded, these methods can be conveniently identified as follows (see Appendix for more details):

- **Proportional rollback:** This AQAP is based on the assumption that the air quality data reported by each monitoring site under attainment conditions will be proportional (relative to each time period) to the data reported under baseline conditions. In the case of 1-hour concentration data, the adjustment equation is simply

  $$\text{Adjusted Ozone} = \rho(s) \times \text{Current Ozone},$$

  where $\rho(s)$ is adjustment factor specific to scenario s. This adjustment factor $\rho(s)$ term can be calculated by the expression

  $$\rho(s) = O_{\max}(s)/O_{\max}(b),$$

  where $O_{\max}(s)$ is a new ozone regulation value and $O_{\max}(b)$ is the current AQI value. Since this AQAP applied a community-specific adjustment factor to all ozone concentrations, the adjusted data exhibited the same degree of reduction at the every percentiles of the distribution.

- **Proportional rollback with background:** This AQAP applies the proportionality assumption to only portion of the concentration that lies above a specified background level. In the case of 1-hour concentration data, the adjustment equation can be expressed as

  $$\text{Adjusted Ozone} = BG + \rho(s) \times (\text{Current Ozone} - BG),$$

  where BG is a background ozone level and the adjustment factor $\rho(s)$ is

  $$\rho(s) = \begin{cases} \frac{O_{\max}(s)-BG}{O_{\max}(b)-BG} & \text{if Current Ozone} > BG \\ 1 & \text{if Current Ozone} \leq BG \end{cases}.$$

  That is,

  $$O_s(c,t) = \begin{cases} BG + \frac{O_{\max}(s)-BG}{O_{\max}(b)-BG}(O_b(c,t) - BG) & \text{if } O_b(c,t) > BG \\ O_b(c,t) & \text{if } O_b(c,t) \leq BG \end{cases},$$

  where $O_s(c,t)$ is the adjusted ozone concentration and $O_b(c,t)$ is the current ozone concentration.

- **Quadratic rollback:** Duff *et al.* (1998) describes the theoretical basis of the quadratic AQAP and discusses its limitations. In its simplest form, the quadratic AQAP can be expressed by the relationship

$$\text{Adjusted Ozone} = (\alpha(s) - \beta(s) \times \text{Current Ozone}) \times \text{Current Ozone}.$$

The degree of reduction applied to each $O_b(c,t)$ depends on its magnitude. That is, large values of ozone concentration are reduced by a larger degree than small values. The coefficients α and β are positive constants. These coefficients can be obtained by relatively complicated procedure depending on specific AQI values. Since this method doesn't guarantee that the specified AQI of the resulting data set equaled the attainment AQI concentration, adjustment step may be required.

- **Weibull rollback:** To simulate attainment conditions, the Weibull AQAP adjusts each value in the baseline ozone concentration by the equation

$$\text{Adjusted Ozone} = \lambda \times (\text{Current Ozone})^{\kappa},$$

The λ and κ coefficients are functions of the parameters of a Weibull distribution fitted to the baseline ozone data and the value of the characteristic largest value (CLV) for ozone regulatory standard. The procedure requires estimation of shape and scale parameters which characterize the Weibull distribution not only under baseline ozone but also under attainment conditions (i.e., new proposed ozone standard regulation). A small proportional adjustment factor is applied to the data to ensure that the AQI exactly equaled the target AQI value as in quadratic rollback.

2.3. Inferences

Since the rollback adjustment to ozone series is applied to each community differently, the national average relative rate $\boldsymbol{\mu}$ can not be used directly to estimate effect of new regulatory standard on reduction of total non-accidental death. Therefore, we directly calculate expected total non-accidental death under the original ozone process and adjusted (rollbacked) ozone process, respectively.

Suppose that g_c is a rollbak function which adjusts observed ozone concentration to attain a proposed new regulatory for community c. Then, our interest lies on the relationship between expected nonaccidental death before and after rollback. Let $E[\log(\mu_t^c)] = \mathbf{x}_t^c\hat{\boldsymbol{\beta}}^c + \mathbf{M}_t^c\hat{\boldsymbol{\theta}}^c$, where $\mathbf{M}_t^c$ is the design matrix of covariates excluding ozone (i.e., DOW_t, $ns(time, 7/year)$, $ns(T_t^c, 6)$, $ns(D_t^c, 6)$, etc.) and $\mathbf{x}_t^c$ is the design matrix of unconstrained (or constrained) distributed-lag ozones for community c. $\hat{\boldsymbol{\beta}}^c$ and $\hat{\boldsymbol{\theta}}^c$ are corresponding coefficients for $\mathbf{M}_t^c$ and $\mathbf{x}_t^c$, respectively. For the same amount of ozone reduction r for each community c, the expected total death reduction ratio or each community c at time t has

$$1 - \frac{\exp\left((\mathbf{x}_t^c - \mathbf{r})\hat{\boldsymbol{\beta}}^c + \mathbf{M}_t^c\hat{\boldsymbol{\theta}}^c\right)}{\exp\left(\mathbf{x}_t^c\hat{\boldsymbol{\beta}}^c + \mathbf{M}_t^c\hat{\boldsymbol{\theta}}^c\right)} = 1 - \exp\left(-\mathbf{r}\hat{\boldsymbol{\beta}}^c\right)$$

and so the nationally expected total death reduction ratio at time t is $1 - \exp(-\mathbf{r}\hat{\boldsymbol{\mu}})$. However, it is not clear what $\boldsymbol{\mu}$ actually means here. For the nationally expected total death reduction ratio, it would be better to estimate a weighted mean effect over the 98 cities, using weights that are proportional to populations. Even this estimate has still limited practical meaning.

Now on, we consider the unconstrained distributed-lag models for a conveniency but it can be easily applied to the constrained distributed-lag models by reparameterization. In the rollback approach, let z_t be rollbacked ozone value of x_t for community c (i.e., $z_t^c = g_c(x_t^c)$). Then, the expected total deaths after rollback transformation for community c during ozone season is

$$\sum_{t \in T_{O_3}} \exp\left(\sum_{j=0}^{6} \beta_j z_{t-j}^c + \mathbf{M}_t^c \hat{\boldsymbol{\theta}}^c\right) = \sum_{t \in T_{O_3}} \exp\left(\sum_{j=0}^{6} \beta_j g_c(x_{t-j}^c) + \mathbf{M}_t^c \hat{\boldsymbol{\theta}}^c\right),$$

where T_{O_3} is the time index set for ozone season. Here, our main interest lies on log ratio of national expected death before and after rollback transformation during ozone season, which is

$$\log \frac{\sum_{c \in C} \sum_{t \in T_{O_3}} \exp\left(\sum_{j=0}^{6} \beta_j z_{t-j}^c + \mathbf{M}_t^c \hat{\boldsymbol{\theta}}^c\right)}{\sum_{c \in C} \sum_{t \in T_{O_3}} \exp\left(\sum_{j=0}^{6} \beta_j x_{t-j}^c + \mathbf{M}_t^c \hat{\boldsymbol{\theta}}^c\right)}$$

$$= \log \sum_{c \in C} \sum_{t \in T_{O_3}} w_{c,t} \exp\left(\sum_{j=0}^{6} \beta_j (z_{t-j}^c - x_{t-j}^c)\right), \tag{2.4}$$

where C is index set for communities included in NMMAPS data and $w_{c,t}$ is the weight of community c at time t. That is,

$$w_{c,t} = \frac{\exp\left(\sum_{j=0}^{6} \beta_j x_{t-j}^c + \mathbf{M}_t^c \hat{\boldsymbol{\theta}}^c\right)}{\sum_{c \in C} \sum_{t \in T_{O_3}} \exp\left(\sum_{j=0}^{6} \beta_j x_{t-j}^c + \mathbf{M}_t^c \hat{\boldsymbol{\theta}}^c\right)}.$$

The posterior distribution of the log ratio of national expected death before and after rollback transformation during ozone season, equation (2.4), can be obtain by MCMC approach. At first, $\boldsymbol{\beta}$ can be generated from posterior distribution $\pi(\boldsymbol{\beta}|\mathbf{Y})$, which can be well approximated by $\pi(\boldsymbol{\beta}|\hat{\boldsymbol{\beta}})$, with an additional prior distribution for $(\boldsymbol{\mu}, \Omega)$. This can be performed by fully MCMC (Gibbs sampling) method or TLNISE (two level Normal independent sampling estimation) algorithm, which is efficient and easy to apply (Everson and Morris 2000). However, it is not the only way of making these calculations. A non-Bayesian calculation based on restricted maximum likelihood (REML) produces similar results. Then, the posterior distribution of the log ratio of national expected death before and after rollback transformation can be constructed based on

$$\log \frac{\sum_{c \in C} \sum_{t \in T_{O_3}} \exp\left(\sum_{j=0}^{6} \beta_j^{(i)} z_{t-j}^c + \mathbf{M}_t^c \hat{\boldsymbol{\theta}}^c\right)}{\sum_{c \in C} \sum_{t \in T_{O_3}} \exp\left(\sum_{j=0}^{6} \beta_j^{(i)} x_{t-j}^c + \mathbf{M}_t^c \hat{\boldsymbol{\theta}}^c\right)},$$

where $\boldsymbol{\beta}^{(i)}$ is the sample from $\pi(\boldsymbol{\beta}|\mathbf{Y})$ or $\pi(\boldsymbol{\beta}|\hat{\boldsymbol{\beta}})$ for $i = 1, \ldots, N$ and N is the number of MCMC samples.

3. Results

To asses effect of proposed new regulatory, we make use of expected total death reduction ratio. Table 3.1 and Table 3.2 summarize posterior means and 95% credible intervals of total mortality per 1000 deaths during 1998-2000 using unconstrained distributed-lag models for common rollback and city-specific rollback approaches, respectively. In common rollback, All the Bayesian credible intervals have lower limits > 0, indicating that the reduction is statistically significant. Lower regulation increases the reduction in mortality, as expected and general pattern similar to CDL. Over all models and rollback functions, the point estimates for reduction range roughly 1.1-2.5 for 75ppb, 1.2-3.6 for 70ppb and 2.4-6.2 for 60 ppb. In city-specific rollback, the point estimates for reduction range roughly 1.0-2.1 for 75ppb, 1.4-2.8 for 70ppb and 2.9-4.8 for 60 ppb over all rollback functions. Different rollbacks provide different posterior city-specific variance of the relative risks. As a covariate, we considered daily maximum ozone concentration and daily 8-hour maximum ozone concentration instead of daily average ozone concentration. Table 3.3 shows that daily maximum ozone and daily 8-hour maximum provide more mortality reduction. In addition to Bayesian inference, we also apply different inference methods such as simple MLE and pooled MLE. Both show similar reduction effect (see Table 3.4). There are still several issues on background level in proportional rollback. Table 3.5 presents mortality reduction for different background ozone levels: 0, 10, 20, 30, 40 ppb.

Table 3.1 Posterior means and 95% CI of total mortality reduction per 1000 deaths (1998-2000): common rollback.

Model	Regulation	Proportional	Prop with BG	Quadratic	Weibull
	level 75	1.87	1.09	0.95	-0.62
		(1.07, 2.62)	(0.62, 1.53)	(0.54, 1.35)	(-1.18, -0.11)
CDL	level 70	2.86	1.66	1.46	0.60
		(1.65, 4.09)	(0.95, 2.39)	(0.84, 2.08)	(0.10, 1.09)
	level 60	4.92	2.86	2.51	2.98
		(2.84, 7.02)	(1.64, 4.09)	(1.43, 3.61)	(1.53, 4.30)
	level 75	1.91	1.11	0.98	-0.62
		(1.15, 2.72)	(0.66, 1.59)	(0.58, 1.39)	(-1.17, -0.07)
UDL	level 70	2.92	1.70	1.49	0.59
		(1.66, 4.14)	(0.97, 2.41)	(0.84, 2.10)	(0.10, 1.09)
	level 60	5.01	2.92	2.56	3.05
		(2.93, 7.19)	(1.66, 4.23)	(1.49, 3.70)	(1.73, 4.38)

Table 3.2 Posterior means and 95% CI of total mortality reduction per 1000 deaths (1998-2000): city-specific rollback.

Model	Regulation	Proportional	Prop with BG	Quadratic	Weibull
	level 75	1.96	1.20	0.98	-0.52
		(1.06, 2.92)	(0.61, 1.79)	(0.51, 1.46)	(-1.33, 0.25)
UDL	level 70	2.75	1.66	1.38	0.44
		(1.47, 4.02)	(0.87, 2.46)	(0.74, 2.03)	(-0.36, 1.26)
	level 60	4.62	2.76	2.40	2.67
		(2.64, 6.69)	(1.58, 4.06)	(1.36, 3.52)	(1.38, 3.99)
	level 75	1.96	1.19	0.98	-0.51
		(0.93, 2.91)	(0.52, 1.79)	(0.45, 1.46)	(-1.36, 0.36)
CDL	level 70	2.78	1.69	1.40	0.45
		(1.50, 3.96)	(0.88, 2.42)	(0.74, 1.99)	(-0.42, 1.23)
	level 60	4.81	2.88	2.50	2.79
		(2.66, 7.05)	(1.55, 4.26)	(1.36, 3.70)	(1.41, 4.31)

Table 3.3 Posterior means and 95% CI of total mortality reduction per 1000 deaths (1998-2000): city-specific rollback and CDL model.

Covariate	Regulation	Proportional	Prop with BG	Quadratic	Weibull
Daily Ave	level 75	1.96	1.19	0.98	-0.51
		(0.93, 2.91)	(0.52, 1.79)	(0.45, 1.46)	(-1.36, 0.36)
	level 60	4.81	2.88	2.50	2.79
		(2.66, 7.05)	(1.55, 4.26)	(1.36, 3.70)	(1.41, 4.31)
Daily Max	level 75	2.32	1.91	1.66	2.48
		(1.54, 3.14)	(1.26, 2.59)	(1.09, 2.27)	(1.62, 3.40)
	level 60	6.19	5.10	4.25	5.13
		(4.11, 8.31)	(3.33, 6.87)	(2.79, 5.75)	(3.41, 6.91)
Daily 8hr Max	level 75	2.10	1.61	1.36	1.90
		(1.26, 2.92)	(0.96, 2.23)	(0.79, 1.94)	(1.13, 2.67)
	level 60	5.53	4.23	3.43	4.34
		(3.37, 7.50)	(2.52, 5.76)	(1.99, 4.69)	(2.52, 5.91)

Table 3.4 Posterior means and 95% CI of total mortality reduction per 1000 deaths (1998-2000): city-specific rollback and CDL model.

Analysis	Regulation	Proportional	Prop with BG	Quadratic	Weibull
Bayesian	level 75	1.96	1.19	0.98	-0.51
		(0.93, 2.91)	(0.52, 1.79)	(0.45, 1.46)	(-1.36, 0.36)
	level 60	4.81	2.88	2.50	2.79
		(2.66, 7.05)	(1.55, 4.26)	(1.36, 3.70)	(1.41, 4.31)
MLE	level 75	2.23	1.31	1.09	-0.30
		(1.14, 3.21)	(0.62, 1.91)	(0.54, 1.58)	(-1.15, 0.48)
	level 60	5.07	2.93	2.52	3.03
		(3.00, 7.28)	(1.65, 4.29)	(1.42, 3.68)	(1.69, 4.37)
Pooled MLE	level 75	1.92	1.16	0.95	-0.50
		(1.79, 2.05)	(1.09, 1.24)	(0.89, 1.02)	(-0.61, -0.38)
	level 60	4.65	2.78	2.40	2.69
		(4.37, 4.92)	(2.62, 2.93)	(2.27, 2.54)	(2.48, 2.88)

Table 3.5 Posterior means and 95% CI of total mortality reduction per 1000 deaths (1998-2000): proportional rollback with background 0, 10, 20, 30, 40 ppb.

Background	0 ppb	10 ppb	20 ppb	30 ppb	40 ppb
Prop with BG	1.96	1.52	1.19	0.85	0.60
(Regulation 75 ppb)	(0.93, 2.91)	(0.75, 2.33)	(0.52, 1.79)	(0.39, 1.32)	(0.26, 0.95)

4. Discussion

There can be several sensitivity issues in this model. Different time lag models with the constrained / unconstrained distributed lags can be considered. We may need to deal with high temperature days. For example, we can drop top 1 % or over 29°C for each city. PM_{10} is another important co-pollutant in the model(e.g. see Bell *et al.* 2004). Using respiratory deaths instead of non-accidental deaths may provide useful results. It is also important to decide reasonable background ozone levels. Collinearity between ozone and other covariates such as temperature should be checked.

Although any spatial structure was not considered here, regional or spatial structure can be implanted and analyzed. To introduce uncertainty in ozone process itself in rollback, we can consider parametric rollback approach using quantile matching method. In that case, it can be assumed that rollback will not change the distribution but only parameters and rollback is not deterministic any more. This approach can be extended to Bayesian framework by considering appropriate prior distributions of parameters.

Appendix: Rollback procedures

- Air quality indicator (AQI):

$$CLVOH = \delta(\log(n))^{1/\kappa},$$

where κ and δ are parameters of Weibull distribution based on hourly averaged values and n is # of hours

$$CLVOHDM = \delta\left[-\log\left(1-\frac{N-1}{N}\right)^{1/24}\right]^{1/\kappa},$$

where κ and δ are parameters of Weibull distribution based on daily maximum 1-hour averaged values and N is # of days.

- Proportional rollback

$$O_s(c,t) = \rho(s) \times O_b(c,t),$$

where $O_b(c,t)$ is the baseline 1-hour ozone at community c and hour t, $O_s(c,t)$ is the adjusted 1-hour ozone at community c and hour t under air quality scenario s, $\rho(s)$ is an adjust factor specified to scenario s and

$$\rho(s) = O_{\max}(s)/O_{\max}(b),$$

where $O_{\max}(s)$ is a new ozone regulation value and $O_{\max}(b)$ is the baseline AQI value.

- Proportional rollback with constant background concentration

$$O_s(c,t) = BG + \rho(s) \times CDIF_b(c,t),$$

where BG is the assumed background concentration,

$$CDIF_b(c,t) = O_b(c,t) - BG$$

and

$$\rho(s) = \begin{cases} \frac{O_{\max}(s)-BG}{O_{\max}(b)-BG} & CDIF_b(c,t) > 0 \\ 1 & CDIF_b(c,t) \le 0 \end{cases}.$$

That is,

$$O_s(c,t) = \begin{cases} BG + \frac{O_{\max}(s)-BG}{O_{\max}(b)-BG}(O_b(c,t)-BG) & O_b(c,t) > BG \\ O_b(c,t) & O_b(c,t) \le BG \end{cases}.$$

- Quadratic rollback

$$O_s(c,t) = [\alpha - \beta \times O_b(c,t)] \times O_b(c,t),$$

where α and β are positive constants.

1. $CAF = CAQI_s/CAQI_b$, where $CAQI_b$ and $CAQI_s$ are the current AQI value and a new ozone regulation value respectively.
2. $TAQI_a(c) = CAF \times AQI_b(c)$, where $TAQI_a(c)$ is target value for AQI under attainment conditions and $AQI_b(c)$ is EH4LDM of daily maximum 8-hour ozone under baseline conditions.
3. Let $S = TAQI_a(c)$. Let J be maximum 1-hour ozone. For each 8-hour ending at hour i, calculate $I_i =$ mean of the 1-hour ozone $Q_i =$ mean of squares of the 1-hour ozone $X_i = 2 \cdot J \cdot I_i - Q_i$ $Z_i = (I_i - S)/Q_i$
4. Let B be the 4^{th} largest daily maximum value of Z_i.
5. Let X be the 4^{th} largest daily maximum value of X_i.
6. Let m be the index value i for the 8-hour period associated with X.
7. $V = 2 \cdot J \cdot S/X$
8. Let x_t be unadjusted 1-hour ozone at time t. Then,

$$y_t = \begin{cases} x_t - Bx_t^2 & V \geq 1 \\ Vx_t - ([VI_m - S]/Q_m)x_t^2 & V < 1 \end{cases}.$$

9. Let $PAQI_s(c)$ be the 4^{th} largest 8-hour daily maximum concentration of y_t.
10. Let z_t be adjusted 1-hour ozone concentration. Then,

$$z_t = \frac{TAQI_a(c)}{PAQI_s(c)} y_t.$$

- Weibull rollback

$$O_s(c,t) = \alpha \times O_b(c,t)^{\beta},$$

where α and β are functions of the parameters of a Weibull distribution fit to the baseline data and CLV predicted to occur under attainment conditions.

1. $CAF = CAQI_s/CAQI_b$, where $CAQI_b$ and $CAQI_s$ are the current AQI value and a new ozone regulation value respectively.
2. $TAQI_a(c) = CAF \times AQI_b(c)$, where $TAQI_a(c)$ is target value for AQI under attainment conditions and $AQI_b(c)$ is EH4LDM of daily maximum 8-hour ozone under baseline conditions.
3. $ACLV1_{NAAQS}(c) = TAQI_{NAAQS}(c) \times CLV_1(c)/EH4LDM(c)$, where $CLV_1(c)$ and $EH4LDM(c)$ are CLV of daily maximum 1-hour and the 4^{th} largest 8-hour ozone under baseline conditions respectively.
4. Estimate the Weibull scale parameter δ and shape parameter κ based on baseline 1-hour data
5. Calculate

$$\delta' = CAF \times \delta$$

and

$$\kappa' = \frac{\log(\log(n))}{\log\left(\frac{ACLV1_{NAAQS}(c)}{\delta'}\right)}.$$

6. Let x_t be unadjusted 1-hour ozone at time t. Then,

$$y_t = \delta' \left(\frac{x_t}{\delta}\right)^{\kappa/\kappa'}.$$

7. Let $PAQI_s(c)$ be the 4^{th} largest 8-hour daily maximum concentration of y_t.
8. Let z_t be adjusted 1-hour ozone concentration. Then,

$$z_t = \frac{TAQI_a(c)}{PAQI_s(c)} y_t.$$

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