Abstract

Perhaps the clearest indications of adverse environmental health effects have been responses to short-term excursions in ambient air quality or temperature as deduced from time-series analyses of exposed populations. However, current analyses cannot characterize the prior health status of affected individuals. We used data on daily elderly death counts, ambient air quality indicators, and temperature in Philadelphia, Chicago, and Atlanta to estimate the daily numbers of frail elderly at-risk of premature mortality, their remaining life expectancies, and environmental effects on life expectancy. These unobserved frail populations at-risk were estimated using the Kalman filter. Frail life expectancies range from 13-16 days. Despite substantial differences in demography and environmental conditions in the three cities, frail life expectancies and contributions of ambient conditions are remarkably similar. The loss in frail life expectancy is approximately 12 hours. Conventional time-series analyses of air pollution effects report similar increases in daily mortality associated with air pollution, but our new model shows that such acute environmental risks are limited to a small fraction of the elderly population whose deaths were imminent in any event. This paradigm shift offered by the
Kalman filter provides context to previous estimates of acute associations of air pollution with mortality.

Key words: life expectancy, daily mortality, frailty, temperature, particulate matter, ozone, time series
1. Introduction

The dramatic mortality increase during the severe polluted fog episode of 1952 in London provided convincing evidence of the potential lethality of air pollution, especially since autopsies were performed. However, such confirmation is not possible under more normal environmental conditions during which only a small fraction of the population may be affected; thus, the prior health status of affected individuals cannot be determined. Since those early times the “mortality displacement” or “harvesting” hypothesis has been considered, in which pollution-associated deaths were advanced by only a few days or weeks, the increased mortality during polluted days having been compensated by corresponding decreases during subsequent cleaner periods. However, time-series studies that considered lag periods of up to several weeks provide evidence to the contrary, such that pollution-associated deaths should indeed be considered “excess”. (Schwartz, 2000).

Nevertheless, assessments of societal impacts of air pollution conclude that loss in remaining life expectancy is a more relevant metric than numbers of premature deaths (Hammitt, 2007; Rabl et al., 2011). Murray and Nelson (2000) developed a new time series model based on the Kalman filter that estimates losses in daily life expectancy, using data on daily pollution and mortality from Philadelphia (1974-88). These losses ranged up to about 2 days. The results showed that elderly (ages 65+) deaths emanate from a fluctuating frail and unobserved subpopulation for which remaining life expectancies are estimated to be only a few weeks. This frailty hypothesis was then supported by a more generalized model that considers both frail and non-frail elderly.
deaths: the latter were shown to comprise only a small fraction of total elderly deaths (Murray and Lipfert, 2012)

The purpose of this study is twofold. First, we extend the Murray-Nelson model to consider two more cities to determine whether the conclusions from Philadelphia apply to other cities. We analyze data from Cook County (Chicago), IL, (1987-2000) and the four-county metropolitan area of Atlanta, GA (1998-2007). These locations were selected because the required data are available and to examine possible geographic heterogeneity and differences among various time periods. The Philadelphia study focused on total suspended particulates (TSP) and ozone. TSP is currently considered to be an obsolete measure of particulate matter. For Chicago and Atlanta, we have much finer measures of particulate matter. In Chicago, PM$_{10}$, O$_3$, SO$_2$, NO$_2$, and CO were considered. These and other pollutants including fine particles (PM$_{2.5}$) were considered in Atlanta. The PM$_{2.5}$ data available for Chicago were too sparse (17% of the total period) for a valid analysis.

The second purpose of this paper is to introduce our econometric model to environmental economists. Our econometric model is based on the Kalman filter, which has been widely used by econometricians since the 1970s, especially for models with unobserved components, but is rarely used in epidemiological studies. Our econometric model assumes that there is an unobserved population of frail, or at-risk, elderly people. Therefore our framework directly lends itself to the machinery of the Kalman filter, which we use to estimate the effects of pollution and temperature on frail life expectancy.
2. The Model

The Murray-Nelson model is based on 3 assumptions.

1. A frail population exists that we identify as a subset of the elderly population (over 65) whose life expectancy is short, even in the absence of pollution exposure. This population cannot be observed but can be estimated with our framework as outlined below.

2. All deaths, including those associated with air pollution and temperature, come from this at-risk population.

3. Once one transitions from being healthy to being frail, there is no recovery from this status.

Our model starts with the following equation:

\[ P_t = P_{t-1} + N_t - D_t \]  

which states that the population at-risk (PAR) today \( P_t \) is its value yesterday \( P_{t-1} \), augmented by new entrants, \( N_t \), and depleted by deaths \( D_t \). This is an accounting identity that holds for any population. Only mortality in Equation (1) is observed.

Mortality is influenced by atmospheric variables through a hazard function that operates on the at-risk population. Listing atmospheric variables in a vector denoted \( x_t \), we assume the hazard function to be the linear combination of these variables, denoted \( (\gamma'x_t) \). The elements of the hazard function will contain pollution and temperature variables, plus various moving averages of these variables. The elements of the vector \( \gamma \) are coefficients that indicate how each atmospheric variable affects mortality. The hazard rate is the value of the hazard function at period \( t \) and it is the expected fraction of deaths in the at-risk population on that date. Some deaths will result from other factors that affect mortality but which we have not included in \( x_t \), so we will augment our mortality
equation below with an error term, which is the difference between actual and expected mortality. Our mortality equation is thus:

\[ D_t = (\gamma' x_t) P_{t-1} + e_t \]  

(2)

This states that all mortality stems from the PAR, save for the error term. Life expectancy is calculated as the inverse of this hazard function, which includes a constant term and functions of temperature and air pollution that may be averaged over periods of several days or weeks in order to consider delayed responses.

Our baseline model employs the following hazard function:

\[ (\gamma' x_t) = \gamma_0 + \gamma_1 x_{t_r} \]

In this model, \( \gamma_0 \) is the constant probability of death in the absence of environmental effects, and \( \gamma_1 \) the marginal environmental effect of \( x_{t_r} \) (e.g. particulate matter or temperature) on daily mortality. Equation (2) states that the frail status of those elderly subjects in the at-risk pool is a prerequisite for death.

New members of the at-risk population are assumed to enter as follows:

\[ N_t = N + \eta_t \]  

(3)

Equation (3) states that on average \( N \) people enter the at-risk pool daily, with random error \( \eta_t \). This model does not allow daily environmental conditions to influence this rate of entry.

Since the at-risk population \( P_t \) and new entrants \( N_t \) are necessarily unobserved, the parameters of this model cannot be estimated by conventional methods such as least squares or Poisson regression. The Kalman filter is therefore useful in this situation, as it allows direct estimation of the unobserved at-risk population and new entrants, as well as
of the impact of environmental variables on daily mortality and life expectancy. The mean life expectancy of subjects in the population at risk may be calculated as the reciprocal of the estimated mean hazard rate.

Our model is quite straightforward to cast into Kalman’s state space framework. Equation (1) is the state, or transition equation, that describes how the unobserved population evolves. Equation (2) is the observation, or measurement equation, that relates observed mortality to PAR.

Once the model is cast into state space form, we can use the Kalman filter to estimate the parameters of the hazard function, the unobserved PAR and its life expectancy. As is the typical practice, we first estimate the parameters of the model via maximum likelihood estimation. Taking these estimates as the true parameter values, we then “run” the Kalman filter to get the minimum MSE estimate of \( P_t \).

We also consider a “generalized” model that includes the features above, plus an additional mortality term for non-frail subjects \((\delta' x_t)\) that does not depend upon the population at risk and thus resembles conventional time-series analysis:

\[
D_t = (\gamma' x_t) P_{t-1} + e_t + \delta' x_t \tag{4}
\]

This model allows a direct comparison between our frailty-based death hazard function \((\gamma' x_t)\) in Equation (2) with conventional time-series models \((\delta' x_t)\) that do not distinguish between deaths of (presumably) healthy individuals and of those that had been compromised previously.

To evaluate the results of the generalized model (4), we compute the “death fraction”, defined as the ratio of the mean value of \((\delta' x_t)\) to total daily deaths, which is a measure of the average relative mortality contribution of non-frail deaths.
3. Data

Table 1 compares the characteristics of these three cities, as obtained from US Census and other sources, and Table 2 presents summary statistics of the data used in the analyses. In Philadelphia, where city and county are conterminous, air quality data were obtained from a single monitoring station, 1974-88 \( (T = 5136) \). The 1987-2000 Chicago data (actually for Cook County, IL) were obtained from the database compiled by the National Mortality and Morbidity Air Pollution System (NMMAPS), which is based on all applicable monitoring stations within a given area \( (T = 5114) \). The 1998-2007 \( (T = 3440) \) Atlanta data were derived from a single research-grade monitoring station in the urban center near the border between Cobb and DeKalb Counties, GA, operated on behalf of the Electric Power Research Institute. The mortality and demographic data for Atlanta in Table 1 are sums or population-weighted averages for Cobb, DeKalb, Fulton, and Gwynnett Counties, GA, within the Atlanta metropolitan area and hereafter referred to as “Atlanta.”

In terms of demography (Table 1), Philadelphia has the highest population density and the lowest mean income level. By contrast with Chicago and Philadelphia, the Atlanta data include suburbs and have lower percentages in poverty status. Elderly mortality rates are similar in all three locations, which are racially mixed and becoming more so over time; Philadelphia has the lowest fractions of Caucasians. The largest numbers of deaths are in Chicago (i.e., Cook County), which should provide the strongest statistical significance levels. The Atlanta area has the shortest period of record.

Lipfert et al. (2000) found similar relationships between 1992-1995 Philadelphia mortality and various measures of PM including fine particles and TSP. This suggests
that TSP is an acceptable PM indicator in Philadelphia to be compared with the effects of PM$_{10}$ in the other cities (see Table 5 of that paper).

Considering that the annual average peak ozone is about twice the mean, these three cities are remarkably similar in terms of ambient air quality for gaseous pollutants (Table 2). However, there are differences in particulate levels and in climate. Chicago also suffered a severe heat wave in the summer of 1995, with large increases in daily death counts.

Correlation coefficients among the key variables for each city are listed in Table 3 for each pair of variables, to facilitate comparisons by city. TSP values are shown for Philadelphia, PM$_{10}$ for Chicago and Atlanta. Complete PM$_{2.5}$ data were only available in Atlanta. In general, the correlations are quite similar among the three cities, which is surprising given the differences in climate and pollution sources. Note that daily mortality is either negatively or uncorrelated with each of the environmental variables in all 3 cities, largely because of the seasonal cycles and higher pollution values in summer as seen by the positive correlations between pollution and temperature. This implies that controlling for season or temperature may be very important for accurate estimates of pollution effects. Also, the high correlation between PM$_{2.5}$ and PM$_{10}$ in Atlanta implies that it may be difficult to distinguish their separate effects.

Regarding seasonal patterns, Murray and Lipfert (2010) found evidence of seasonal bias in some of their mortality parameter estimates. They investigated the use of trigonometric functions and quarterly dummy variables for this purpose, which made little difference in the final conclusions. Accordingly, we use a quadratic model in temperature to control for season.
4. Results

4.1 Results from the Murray-Nelson Model

Tables 4(a-c) compares the results of each Kalman filter model run across cities for the three key model output parameters: (a) size of the population at-risk, (b) baseline life expectancies for the frail subpopulation, (c) losses in life expectancy associated with air pollution. The model runs vary in terms of the pollutants considered and the lengths of moving averages used for pollution and for ambient temperature.

Populations at risk (Table 4a) are approximately proportional to the total elderly population in each city, with ratios of 0.00204, 0.00167, and 0.00243 respectively. However, there is little variation among the models run for each city. Frail life expectancies at mean observed pollution levels are on the order of two weeks (Table 4b), are more uniform and tend to increase with the length of MAs for temperature. Increased pollution MAs have small and mixed effects. Losses in life expectancy associated with maximum observed pollution (Table 4c) are quite heterogeneous, with the largest effects seen with Philadelphia TSP, up to two days. For Atlanta and Chicago, losses are rarely more than twelve hours.

4.2 Generalized Model Results

The generalized model tests the hypothesis that all elderly deaths are preceded by a period of severe frailty that severely curtails life expectancy (Equation 4). We first tested this hypothesis in Philadelphia, for which 98.6% of the deaths were preceded by frailty and assigned to the PAR. We found 99% of the deaths for Chicago and 99.7% for the Atlanta area. These results are reported in Table 5. We thus conclude that the hypothesis of prior frailty is confirmed and that non-frail people are not at risk in these three cities.
5. Implications

The findings of this research have profound implications for the evaluation of air pollution health effects. Premature mortality is the controlling factor for cost-benefit analysis and epidemiology is the only practical source of such information. In order to achieve statistically significant results, typical short-term epidemiology studies must involve hundreds of thousands of deaths of which thousands may be attributed to air pollution. Information on individual health status is thus inaccessible but, based on observed daily fluctuations, the Murray-Nelson model provides estimates of the subpopulations most at risk as the next best thing. The miniscule sizes of such populations, 0.2% of the elderly, indicate that these individuals must indeed be among the most vulnerable and that the conventional assumption of random individuals at risk is untenable. Mean life expectancy at age 65 is about 15 years but individual deaths may occur the next day or after 40 years. Our frail life expectancy estimates of two weeks must thus pertain to already severely impaired individuals, leading to the conclusion that healthy individuals are not at risk from daily variations in environmental conditions, as established by the generalized model results. Since long-term studies include short-term effects like these, a portion of the estimated long-term effects must similarly be limited to previously impaired individuals.

Typical air pollution cost benefit analyses have been based on societal impacts of about $7 million per excess death. These estimates of the value of a statistical life are typically derived from working-age populations, which might involve a loss of say, 25 years in life expectancy. From our estimates the loss would be less than $800 for each
excess death, thus reducing the estimated benefits of air pollution control by about 3 orders of magnitude.

6. Conclusions

We conclude that frail life expectancies estimated from the Murray-Nelson model are similar in each of three cities having different demographic and environmental characteristics and that our model is robust. Frail populations at risk are about 0.2% of the underlying elderly (age 65+) population. Estimated frail life expectancies are on the order of two weeks. Reductions in life expectancy at maximum observed levels of air pollution range from miniscule to up to 2 days, with the largest effects seen in Philadelphia.

Acknowledgments

This research was sponsored in part by the Electric Power Research Institute, under the guidance of Dr. R.E. Wyzga.
Appendix. Other Studies of Air Pollution and Life Expectancy

Smith et al. (1999) used Monte Carlo methods for elderly daily mortality in Chicago and found results similar to ours, while not directly estimating a population at-risk. Knudsen (2004) estimates the effect of ozone and carbon monoxide on frail life expectancy in Toronto, using daily from 1980 through 1994. Like Murray and Nelson (2000), he posits the existence of an at-risk population that is depleted by deaths and replenished by new entrants. In contrast to Murray and Nelson, the mortality observation equation follows a conditional binomial process. New entries are allowed to be a function of covariates, and opposed by the assumption of random new entries of Murray and Nelson (2000). Knudsen’s model is estimated using the Kalman filter, with an identifying assumption that life expectancy of the frail must be between 1 and 21 days. Conditional on this assumption, he estimates life expectancy of the already frail to be 12 days in the summer and 6 days in the winter, with ozone and carbon monoxide reducing these values by a few days.
References


# Table 1  Demographic Characteristics of the Three Cities

<table>
<thead>
<tr>
<th></th>
<th>Philadelphia</th>
<th>Chicago</th>
<th>Atlanta</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1980</td>
<td>1990</td>
<td>2000</td>
</tr>
<tr>
<td>population</td>
<td>1688210</td>
<td>1552572</td>
<td>2099796</td>
</tr>
<tr>
<td>density/mi(^2)</td>
<td>12413</td>
<td>11942</td>
<td>1337</td>
</tr>
<tr>
<td>% Caucasian</td>
<td>58.5</td>
<td>54.7</td>
<td>70.4</td>
</tr>
<tr>
<td>% age 65+</td>
<td>14.1</td>
<td>15.2</td>
<td>8.9</td>
</tr>
<tr>
<td>income/cap</td>
<td>6053</td>
<td>12091</td>
<td>18149</td>
</tr>
<tr>
<td>% in poverty</td>
<td>16.6</td>
<td>16.1</td>
<td>11.9</td>
</tr>
</tbody>
</table>
Table 2. Air Quality, Weather, and Mortality Data Used in Each City

<table>
<thead>
<tr>
<th>Particulates</th>
<th>Philadelphia</th>
<th>Chicago</th>
<th>Atlanta</th>
</tr>
</thead>
<tbody>
<tr>
<td>TSP, ( \mu g/m^3 )</td>
<td>66.2 (25.9)</td>
<td>-----</td>
<td>-----</td>
</tr>
<tr>
<td>PM(_{10}), ( \mu g/m^3 )</td>
<td>-----</td>
<td>33.6 (19.2)</td>
<td>25.1 (11.40)</td>
</tr>
<tr>
<td>PM(_{2.5}), ( \mu g/m^3 )</td>
<td>-----</td>
<td>-----</td>
<td>16.7 (8.1)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Gases</th>
<th>mean</th>
<th>sd</th>
<th>mean</th>
<th>sd</th>
<th>mean</th>
<th>sd</th>
</tr>
</thead>
<tbody>
<tr>
<td>peak O(_3), ppb</td>
<td>44.6 (29.3)</td>
<td>20.0 (10.3)</td>
<td>24.0 (12.5)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CO, ppm</td>
<td>-----</td>
<td>1.07 (0.94)</td>
<td>0.46 (0.33)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NO(_2), ppb</td>
<td>-----</td>
<td>25.5 (7.8)</td>
<td>20.4 (8.41)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SO(_2), ppb</td>
<td>-----</td>
<td>5.1 (3.1)</td>
<td>5.0 (4.6)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Temperature, F</th>
<th>mean</th>
<th>sd</th>
<th>mean</th>
<th>sd</th>
<th>mean</th>
<th>sd</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature, F</td>
<td>63.7 (19.1)</td>
<td>50.2 (19.5)</td>
<td>63.7 (4.6)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Deaths/Day (65+)</td>
<td>35.0 (7.1)</td>
<td>83.3 (12.5)</td>
<td>24.8 (5.5)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Mortality Rate</td>
<td>0.0539</td>
<td>0.0503</td>
<td>0.0549</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( T )</td>
<td>5136</td>
<td>5114</td>
<td>3440</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 3  Correlations among Variables in Each City

<table>
<thead>
<tr>
<th>Variables</th>
<th>Philadelphia</th>
<th>Chicago</th>
<th>Atlanta</th>
</tr>
</thead>
<tbody>
<tr>
<td>PM$_{2.5}$</td>
<td>PM$_{10}$</td>
<td>-----</td>
<td>-----</td>
</tr>
<tr>
<td>temperature</td>
<td>O$_3$</td>
<td>0.72</td>
<td>0.56</td>
</tr>
<tr>
<td>PM$_{10}$,TSP*</td>
<td>O$_3$</td>
<td>0.34*</td>
<td>0.32</td>
</tr>
<tr>
<td>PM$_{2.5}$</td>
<td>O$_3$</td>
<td>-----</td>
<td>-----</td>
</tr>
<tr>
<td>temperature</td>
<td>PM$_{10}$,TSP*</td>
<td>0.28*</td>
<td>0.36</td>
</tr>
<tr>
<td>temperature</td>
<td>PM$_{2.5}$</td>
<td>-----</td>
<td>-----</td>
</tr>
<tr>
<td>mortality</td>
<td>PM$_{10}$,TSP*</td>
<td>0.02*</td>
<td>-0.02</td>
</tr>
<tr>
<td>mortality</td>
<td>PM$_{2.5}$</td>
<td>-----</td>
<td>-----</td>
</tr>
<tr>
<td>mortality</td>
<td>O$_3$</td>
<td>-0.16</td>
<td>-0.18</td>
</tr>
<tr>
<td>mortality</td>
<td>Temperature</td>
<td>-0.28</td>
<td>-0.38</td>
</tr>
</tbody>
</table>

*TSP is used as the particulate measure in Philadelphia
Table 4(a) Estimated Populations at Risk

Moving Average Length

<table>
<thead>
<tr>
<th>Pollutant</th>
<th>Pollutant</th>
<th>Temperature</th>
<th>Philadelphia</th>
<th>Chicago</th>
<th>Atlanta</th>
</tr>
</thead>
<tbody>
<tr>
<td>O₃</td>
<td>1</td>
<td>1</td>
<td>460</td>
<td>1014</td>
<td>388</td>
</tr>
<tr>
<td>O₃</td>
<td>7</td>
<td>1</td>
<td>499</td>
<td>986</td>
<td>387</td>
</tr>
<tr>
<td>O₃</td>
<td>15</td>
<td>1</td>
<td>553</td>
<td>896</td>
<td>386</td>
</tr>
<tr>
<td>O₃</td>
<td>7</td>
<td>3</td>
<td>602</td>
<td>1018</td>
<td>409</td>
</tr>
<tr>
<td>O₃</td>
<td>7</td>
<td>7</td>
<td>557</td>
<td>1119</td>
<td>424</td>
</tr>
<tr>
<td>mean</td>
<td></td>
<td></td>
<td>534</td>
<td>1007</td>
<td>399</td>
</tr>
<tr>
<td>se of mean</td>
<td></td>
<td></td>
<td>25</td>
<td>40</td>
<td>8</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Pollutant</th>
<th>Pollutant</th>
<th>Temperature</th>
<th>Philadelphia</th>
<th>Chicago</th>
<th>Atlanta</th>
</tr>
</thead>
<tbody>
<tr>
<td>PM₁₀</td>
<td>1</td>
<td>1</td>
<td>494*</td>
<td>997</td>
<td>386</td>
</tr>
<tr>
<td>PM₁₀</td>
<td>7</td>
<td>1</td>
<td>501*</td>
<td>969</td>
<td>388</td>
</tr>
<tr>
<td>PM₁₀</td>
<td>15</td>
<td>1</td>
<td>532*</td>
<td>900</td>
<td>390</td>
</tr>
<tr>
<td>PM₁₀</td>
<td>7</td>
<td>3</td>
<td>585*</td>
<td>1026</td>
<td>407</td>
</tr>
<tr>
<td>PM₁₀</td>
<td>7</td>
<td>7</td>
<td>634*</td>
<td>1130</td>
<td>419</td>
</tr>
<tr>
<td>mean</td>
<td></td>
<td></td>
<td>549*</td>
<td>1004</td>
<td>399</td>
</tr>
<tr>
<td>se of mean</td>
<td></td>
<td></td>
<td>27*</td>
<td>42</td>
<td>6</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Pollutant</th>
<th>Pollutant</th>
<th>Temperature</th>
<th>Philadelphia</th>
<th>Chicago</th>
<th>Atlanta</th>
</tr>
</thead>
<tbody>
<tr>
<td>PM₂·₅</td>
<td>1</td>
<td>1</td>
<td>---</td>
<td>---</td>
<td>387</td>
</tr>
<tr>
<td>PM₂·₅</td>
<td>7</td>
<td>1</td>
<td>---</td>
<td>---</td>
<td>388</td>
</tr>
<tr>
<td>PM₂·₅</td>
<td>15</td>
<td>1</td>
<td>---</td>
<td>---</td>
<td>381</td>
</tr>
<tr>
<td>PM₂·₅</td>
<td>7</td>
<td>3</td>
<td>---</td>
<td>---</td>
<td>408</td>
</tr>
<tr>
<td>PM₂·₅</td>
<td>7</td>
<td>7</td>
<td>---</td>
<td>---</td>
<td>421</td>
</tr>
<tr>
<td>mean</td>
<td></td>
<td></td>
<td>---</td>
<td>---</td>
<td>397</td>
</tr>
<tr>
<td>se of mean</td>
<td></td>
<td></td>
<td>---</td>
<td>---</td>
<td>8</td>
</tr>
</tbody>
</table>

* denotes TSP for Philadelphia
Table 4(b)  Estimated Baseline Frail Life Expectancies in Days

Moving Average Length

<table>
<thead>
<tr>
<th>Pollutant</th>
<th>Pollutant</th>
<th>Temperature</th>
<th>Philadelphia</th>
<th>Chicago</th>
<th>Atlanta</th>
</tr>
</thead>
<tbody>
<tr>
<td>O₃</td>
<td>1</td>
<td>1</td>
<td>13.15</td>
<td>12.18</td>
<td>15.50</td>
</tr>
<tr>
<td>O₃</td>
<td>7</td>
<td>1</td>
<td>14.27</td>
<td>11.83</td>
<td>15.48</td>
</tr>
<tr>
<td>O₃</td>
<td>15</td>
<td>1</td>
<td>15.79</td>
<td>10.76</td>
<td>15.45</td>
</tr>
<tr>
<td>O₃</td>
<td>7</td>
<td>3</td>
<td>17.20</td>
<td>12.19</td>
<td>16.35</td>
</tr>
<tr>
<td>O₃</td>
<td>7</td>
<td>7</td>
<td>15.90</td>
<td>13.43</td>
<td>16.94</td>
</tr>
</tbody>
</table>

| PM₁₀      | 1         | 1           | 14.10*       | 11.97   | 15.45   |
| PM₁₀      | 7         | 1           | 14.30*       | 11.67   | 15.51   |
| PM₁₀      | 15        | 1           | 15.20*       | 10.80   | 15.61   |
| PM₁₀      | 7         | 3           | 16.70*       | 12.29   | 16.27   |
| PM₁₀      | 7         | 7           | 18.10*       | 13.57   | 16.76   |

| PM₂₅      | 1         | 1           | ---          | ---     | 15.46   |
| PM₂₅      | 7         | 1           | ---          | ---     | 15.51   |
| PM₂₅      | 15        | 1           | ---          | ---     | 15.23   |
| PM₂₅      | 7         | 3           | ---          | ---     | 16.33   |
| PM₂₅      | 7         | 7           | ---          | ---     | 16.85   |

* denotes TSP for Philadelphia
### Table 4(c)  Estimated Loss in Life Expectancy Maximum Observed Pollution

**Moving Average Length**

<table>
<thead>
<tr>
<th>Pollutant</th>
<th>Pollutant</th>
<th>Temperature</th>
<th>Philadelphia</th>
<th>Chicago</th>
<th>Atlanta</th>
</tr>
</thead>
<tbody>
<tr>
<td>O$_3$</td>
<td>1</td>
<td>1</td>
<td>0.00</td>
<td>0.12</td>
<td>0.22</td>
</tr>
<tr>
<td>O$_3$</td>
<td>7</td>
<td>1</td>
<td>0.83</td>
<td>0.02</td>
<td>0.21</td>
</tr>
<tr>
<td>O$_3$</td>
<td>15</td>
<td>1</td>
<td>0.15</td>
<td>0.15</td>
<td>0.28</td>
</tr>
<tr>
<td>O$_3$</td>
<td>7</td>
<td>3</td>
<td>1.90</td>
<td>0.28</td>
<td>0.52</td>
</tr>
<tr>
<td>O$_3$</td>
<td>7</td>
<td>7</td>
<td>0.72</td>
<td>0.67</td>
<td>0.85</td>
</tr>
</tbody>
</table>

| PM$_{10}$ | 1         | 1           | 0.41*        | 0.05    | 0.25    |
| PM$_{10}$ | 7         | 1           | 0.80*        | 0.26    | -0.01   |
| PM$_{10}$ | 15        | 1           | 2.10*        | 0.02    | -0.32   |
| PM$_{10}$ | 7         | 3           | 1.70*        | 0.15    | 0.22    |
| PM$_{10}$ | 7         | 7           | 2.50*        | 0.41    | 0.42    |

| PM$_{2.5}$| 1         | 1           | ---          | ---     | 0.15    |
| PM$_{2.5}$| 7         | 1           | ---          | ---     | 0.03    |
| PM$_{2.5}$| 15        | 1           | ---          | ---     | -0.01   |
| PM$_{2.5}$| 7         | 3           | ---          | ---     | 0.23    |
| PM$_{2.5}$| 7         | 7           | ---          | ---     | 0.37    |

* denotes TSP for Philadelphia
Table 5. Generalized Model Results

<table>
<thead>
<tr>
<th>pollutant</th>
<th>TSP, O\textsubscript{3}</th>
<th>PM\textsubscript{10}</th>
<th>O\textsubscript{3}</th>
<th>PM\textsubscript{10}</th>
<th>O\textsubscript{3}</th>
</tr>
</thead>
<tbody>
<tr>
<td>% non-frail</td>
<td>1.4</td>
<td>0.08</td>
<td>0.67</td>
<td>0.01</td>
<td>0.3</td>
</tr>
<tr>
<td>pop-at-risk</td>
<td>552</td>
<td>927</td>
<td>906</td>
<td>384</td>
<td>394</td>
</tr>
</tbody>
</table>