Online Appendix: Bringing Satellite-Based Air-Quality Estimates Down to Earth

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I. Concentration-Response Functions

Concentration-response (or "hazard") functions relate exposure to concentrations of a $PM_{2.5}$ to risk of negative health impacts. Notably, no safe threshold has been identified, and some research suggests that marginal benefits from abatement are *decreasing* in baseline concentrations (see, for example, Krewski et al. (2009)). Here, we follow the EPA standard for Regulatory Impact Analysis and assume a log-linear functional form over the range of $PM_{2.5}$ concentrations we observe.

These functions are typically estimated using random-effects Cox proportional-hazard models. Log-linear specifications regress the natural log of mortality risk on $PM_{2.5}$ concentration levels:

$$ln(\lambda(X, PM_{2.5}) = ln(\widehat{\lambda}) + X'\beta + \gamma PM_{2.5},$$

where $\widehat{\lambda}$ is the baseline mortality risk; X is a matrix of covariates that presumably affect mortality; and $PM_{2.5}$ is the pollution concentration level. We are primarily interested in γ which captures the estimated average effect of an incremental change in $PM_{2.5}$ concentrations on mortality (conditional on X.

Taking the ratio of two hazard functions identifies the relative mortality risk (RR) or hazard ratio (HR) between a relatively high concentration of pollution and a low concentration:

$$HR = \frac{\lambda(X, PM_{2.5}^{'})}{\lambda(X, PM_{2.5}^{''})} = exp(\gamma(PM_{2.5}^{''} - PM_{2.5}^{'}))$$

Note that, using the log-linear function of the concentration-response function, an incremental change in pollution concentration will lead to the same value of the hazard ratio, regardless of the baseline level of the concentration.

We use these hazard ratios to evaluate, for a given location, the impact of an incremental change in air pollution concentrations (relative to the baseline concentrations we observe). To implement this empirically, we use mortality relative risk (RR) ratios estimated by two influential studies.

- Krewski et al. (2009) analyze a large, ongoing American Cancer Society Cancer Prevention Study of mortality in adults initiated in 1982. Krewski et al. (2009) incorporate additional years of follow-up and include refinements of statistical methods and incorporate sophisticated control of bias and confounding. Data analyzed included all causes, cardiopulmonary disease (CPD), ischemic heart disease (IHD, reduction of blood supply to the heart, potentially leading to heart attack), lung cancer, and all remaining causes.

  When estimating PM mortality impacts based on the Krewski et al. (2009) study, the U.S. EPA applies mortality risk coefficients stratified by educational attainment. We follow this approach.[1]

- In another influential study, Lepeule

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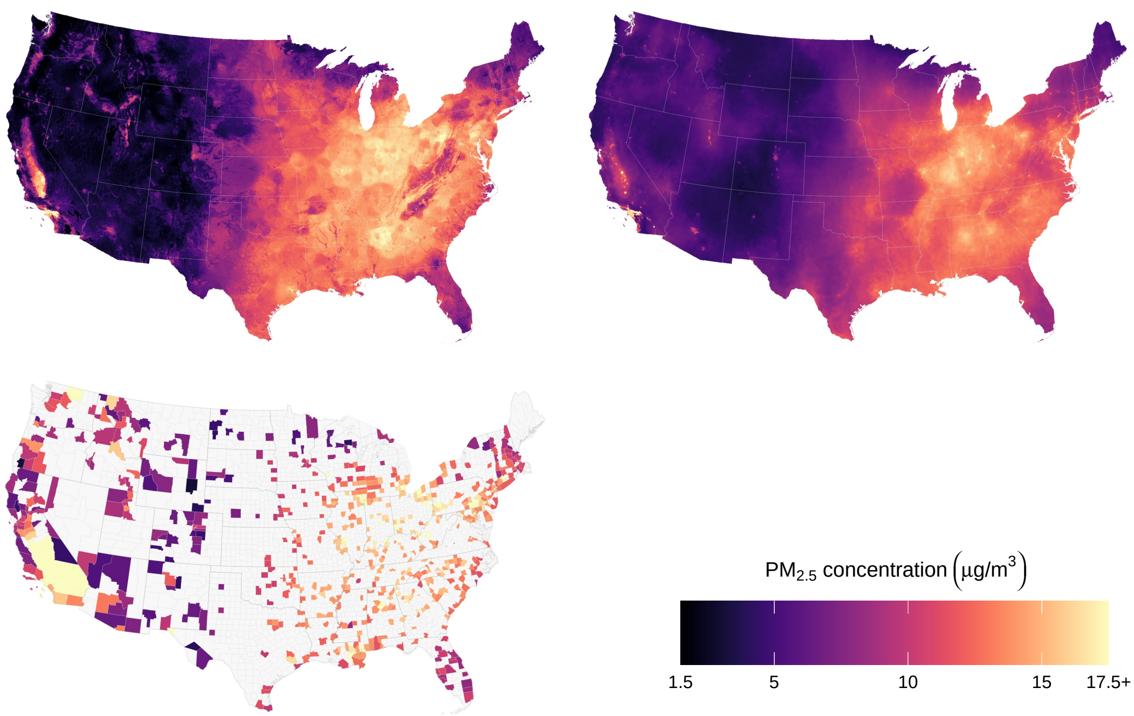
[1] Krewski et al. (2009) find that educational attainment is inversely related to mortality risk. Populations with lower levels of education are more vulnerable to $PM_{2.5}$ related mortality.

et al. (2012) estimate cause-of-death specific hazard ratios. We use these cause-of-death-specific estimates from this study to construct our 'high' mortality impact estimates.

We estimate the census block group mortality rates using the average annual deaths in county i divided by the county population. Following the literature, we focus exclusively on mortality rates associated with cardiovascular diseases, ischemic heart disease and cerebrovascular disease, and respiratory complications. We estimate the mortality impacts of an incremental (i.e., 1 $\mu g/m^3$) reduction in $PM_{2.5}$ concentrations as:

$$\begin{aligned}\Delta Deaths_{ij} =& Pop_{ij} \cdot \lambda_{ij}[1 - \frac{1}{HR_j(C_i - 1)}] \\ =& Pop_{ij} \cdot \lambda_{ij}[1 - exp(-\gamma_j)],\end{aligned}$$

where i denotes county and j denotes the population cohort.



(a) Di et al.

(b) van Donkelaar et al.

(c) EPA Monitor-Based Measurements

Figure 1. : Satellite-Based $PM_{2.5}$ Measurements and EPA AQS Monitoring Network, 2005

Notes: These figures display the 2005 annual mean pollution concentrations from Di et al. (2016), van Donkelaar et al. (2019), EPA-AQS monitors, respectively. We winsorized the EPA monitor data above their 95th percentile (17.5).

(a) Di et al. (b) van Donkelaar et al. (2019)

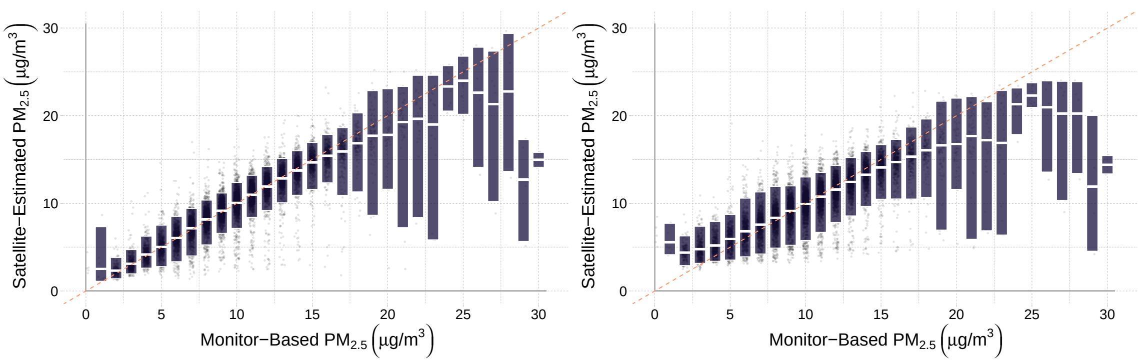


Figure 2. : Comparing $PM_{2.5}$: Monitors' Measurements vs. Satellite-Based Estimates

Notes: These figures display the relationships between satellite-based pollution measurements and monitor based pollution measurements for the 911 census block groups that contain an EPA $PM_{2.5}$ monitor. The blue boxes depict the range of estimates (2.5^{th}–97.5^{th} percentiles) from the satellite-based datasets (y axis) for the given $PM_{2.5}$ level measured by the EPA-AQS monitor (x axis). Source: Authors, Di et al. (2016), van Donkelaar et al. (2019), EPA-AQS.

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