A Spatial Model of Air Pollution: The Impact of the Concentration-Response Function
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Andrew L. Goodkind, Jay S. Coggins, Julian D. Marshall

Abstract: We develop a spatial model to examine policies aimed at reducing ambient concentrations of fine particulates ($PM_{2.5}$), with emissions from many sources that affect many population centers. Two alternative specifications of the relationship between $PM_{2.5}$ concentration and health impacts from Krewski et al. are analyzed: log-linear, which implies downward-sloping marginal benefits of abatement; and log-log, which implies upward-sloping marginal benefits of abatement. A standard assumption would be that the greatest benefit from cleanup would occur in the dirtiest locations. We show, however, that for the log-log (but not log-linear) relationship, the largest risk reductions are achieved from abatement of pollution in the cleanest locations. Our model demonstrates that with a log-log relationship society should prefer lower emissions and lower pollution concentrations than if the relationship is log-linear. Our model also shows that an efficient abatement policy may substantially outperform a uniform pollution standard such as the National Ambient Air Quality Standards (NAAQS).

JEL Codes: H41, I18, Q53

Keywords: Air pollution, Environmental policy, Increasing marginal benefits

THE STANDARD APPROACH to analyzing clean-air policy assumes that the benefit associated with a unit of abatement declines as the air becomes cleaner.[1] That is, the greatest marginal improvements in human health are to be achieved in the dirtiest places. This assumption is based in a particular understanding of the relation-

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1. Or, as in Muller and Mendelsohn (2009), that marginal benefits are constant.

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ship between pollution and human health: that the marginal harm to health grows ever more severe as the level of pollution rises. The traditional view is appealing from an ethical perspective because it means that we should clean the dirtiest places first, thereby protecting those most who are most at risk. In line with this understanding, regulation of harmful pollutants has generally been based on uniform standards such as, in the United States, the National Ambient Air Quality Standards (NAAQS). The NAAQS set limits on pollution concentration that are not to be exceeded in any location.

In this paper we ask, what if the basic understanding regarding the link between pollution exposure and health outcomes is wrong? This question, we argue, is both interesting and relevant to environmental policy. Recent estimates of the concentration-response (C-R) relationship between fine particulates (particulate matter with a diameter less than 2.5 microns, $PM_{2.5}$) and several causes of adult mortality suggest that the C-R function for $PM_{2.5}$ might be strictly concave in concentration. If true, this C-R function would mean that the first unit of abatement yields the smallest improvement in health risk, while the last unit, taking us to a pristine environment, yields the greatest improvement. Crouse et al. (2012), for example, find that the C-R relationship for $PM_{2.5}$ on ischemic heart disease is strictly concave ("supralinear") over ambient concentrations. Supralinear C-R functions across a wide range of $PM_{2.5}$ concentrations (including observations from exposure to ambient air, secondhand smoke, and active smokers) were also found in Ostro (2004) and Pope et al. (2009, 2011).

An interesting question, which economists are hardly equipped to answer, is which physiological pathways could lead to supralinearity. This matter is not well understood in the relevant health literature, but there are some tentative suggestions. Ambrose and Barua (2004, 1735) posit that the "underlying biochemical and cellular processes may become saturated with small doses of toxic components from cigarette smoke causing a nonlinear dose-response on cardiovascular function." Whatever the physiological explanation, supralinear C-R functions are common in studies of mortality from exposure to workplace toxins (Stayner et al. 2003). Among several explanations of the attenuation of the relative risk at higher concentrations, Stayner et al. suggest the possibility of a saturation of enzyme systems, where relative risks increase faster before saturation is reached, and less thereafter. Birnbaum (2012) discusses the "low-dose hypothesis" which indicates that the impacts to human health from exposure to low doses of chemicals may be fundamentally different than what would be expected from the impact at higher doses.

Krewski et al. (2009), in their follow-up to the influential study by Pope et al. (1995), estimate the health risks associated with $PM_{2.5}$ exposure. They present the results of estimates based on two functional forms (see fig. 1). The first form is a log-linear C-R relationship (they call this relationship the "linear" version), which is convex and so leads to the usual form: a marginal benefit function that decreases in abatement. The second form is a log-log relationship (they call this relationship the "log" version), which is concave, or supralinear, and so leads to a marginal benefit

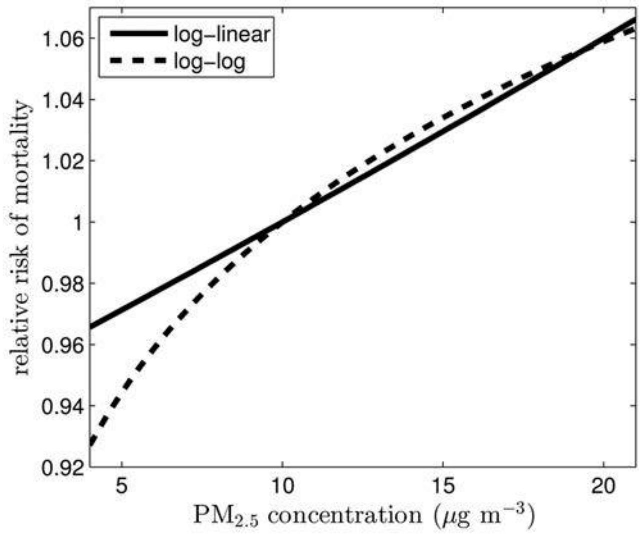

Figure 1. Risk of mortality from $PM_{2.5}$ concentration relative to risk at 10 μg m^{-3} for Krewski et al. (2009) log-linear and log-log concentration-response functions.

function that increases in abatement. Regarding which of the two functions is to be preferred statistically, Krewski et al. (2009, 27) say only that "the logarithmic function was a slightly better predictor of the variation in survival among MSAs than the linear function because the MSA random-effect variance is somewhat smaller (than that for the linear function) for each cause-of-death category except all other causes."

The Krewski et al. study highlights the uncertainty regarding the shape of the C-R function between $PM_{2.5}$ and adult mortality. The difference between the two forms of the C-R function has significant implications for air pollution policy of possibly the most consequential environmental issue affecting human health. Despite the enormous benefits from existing regulations, ambient concentrations of fine particulates remain a major cause of premature mortality in the United States. The Office of Management and Budget estimates that the benefits of EPA regulations on fine particulate concentrations range from $19 billion to $167 billion per year (OMB 2013). The benefits are large because reduced exposure to fine particulates has saved many lives, yet at existing concentrations substantial risks remain. Fann et al. (2012) estimates 130,000 annual cases of premature mortality attributable to fine particulate concentrations. In contrast, the comparative costs for cleanup are quite modest: by OMB's estimates, benefits are 2.6 to 22.9 times larger than costs (OMB 2013). Krewski et al. is central to the analysis of the impacts of exposure to fine particulates. The estimates in Krewski et al. are the latest from an American Cancer Society study, one of two major longitudinal analyses on the link between $PM_{2.5}$ and premature mortality. In the recent regulatory impact analysis by the US EPA (2012, 5-32) recommending a lower standard for fine particulate concentrations, the key parameter was the Krewski et al. log-linear estimate.

The importance of the log-log C-R function is that it calls into question the risks of mortality faced by individuals exposed to low levels of pollution, suggesting that mortality risks may be substantially lower at very low concentrations than at moderate or high concentrations. Why should one care about the risks borne by people exposed to the lowest concentrations, given that most experience higher exposures and correspondingly greater risks? Under the Clean Air Act, the primary goal of pollution control is to protect human health, and the general trend has been toward less pollution and lower risks.[2] In order to arrive at desirable policy outcomes, we must understand the risks at the lowest pollution level being considered. If the log-log C-R function is correct, then the benefits associated with achieving very low pollution levels are even higher than we have thought.[3]

A log-log C-R relationship suggests that regulators should focus not only on reducing risks for people at high concentrations but also on reducing risks for people at low concentrations. Uniform pollution standards like the NAAQS, by their nature, have the effect of aiming abatement resources at those places where concentrations are the highest. As we show here, the uniform standard approach is not necessarily the most appealing from a social welfare perspective if marginal benefits are increasing in abatement. An alternative policy, one that seeks to maximize the aggregate net benefits of abatement, might yield a very different outcome. A policy of maximizing social welfare, as opposed to limiting risks in the dirtiest locations, raises concerns over environmental justice, as it may tend to exacerbate the disparity between the pollution faced by individuals, leading to greater inequality in environmental risk.

We compare the implications for mortality risk of the two functional forms estimated by Krewski et al. (2009) and the socially preferred policies to regulate air pollution in both cases. We devise a simple model that captures the spatial aspects of air pollution over a region with many sources of pollution and many receptors. An efficient abatement policy is examined that controls pollution at each individual

2. For instance, emissions of sulfur dioxide (one of the main contributors to fine particulate concentrations) in the United States have dropped from 23 million tons in 1990 to 5.5 million tons in 2012 (NEI 2013). This drop has contributed to the 33% decrease in the US national average concentration of $PM_{2.5}$ from 13.8 $\mu g\ m^{-3}$ in 2000 to 9.3 $\mu g\ m^{-3}$ in 2012 (EPA 2013).

3. In an analysis of the effects of lead exposure on children's IQ, Rothenberg and Rothenberg (2005), find that a model using the log of lead exposure is a significantly better fit of the data than a model with a linear lead relationship. The estimated benefits in the United States from the drop in lead concentrations to very low levels is 2.2 times greater with the log model than with linear.

source and maximizes the social welfare of the individuals and industries in the region. The efficient policy is compared to a uniform standard, under which a cap is placed upon concentrations across the region, and a uniform tax, where a fee is levied on each unit of pollution emitted. The three policies are compared for both C-R functional forms based on total social welfare, the average concentration of pollution in receptors, and the level of environmental inequality across receptors.

We find that society should prefer significantly lower emissions, and correspondingly lower ambient concentrations, of air pollution if the log-log C-R function is correct than if the log-linear C-R function is correct. Our findings underscore the importance of identifying the true shape of the C-R function between fine particulates and adult mortality.

With a log-log C-R function, we find that the efficient abatement policy performs substantially better than the uniform standard in maximizing social welfare and limiting the exposure to pollution. The efficient policy is also preferred to a uniform tax policy across the region, suggesting that there is substantial heterogeneity in marginal damages across sources. Surprisingly, the environmental inequality concerns with the efficient policy are slightly less than with the uniform standard. Pollution concentration reductions in the cleanest receptors provides benefits to all surrounding locations due to the widespread dispersion of the pollutant. In obtaining the greatest risk reductions in the cleanest locations, significant pollution concentration reductions are achieved across the map.

1. A MULTIPLE-RECEPTOR, MULTIPLE-SOURCE MODEL

This paper presents a model that compares the outcomes from air pollution regulation policies using either a log-linear or log-log C-R relationship between fine particulate concentrations and adult mortality. The model simulates the dispersion of emissions from many sources (denoted by subscript j) located across a rectangular geographic region, and calculates the resulting change in pollution concentrations in all receptors (denoted by subscript i) in this region.

The region is separated into N identically sized grid squares. Each square can be both a source and receptor of pollution ($i, j = 1, \ldots, N$). In each grid square there is a population, Pop_i, and an aggregate mass emission rate, e_j, of $PM_{2.5}$, a primary conserved air pollutant. The model simulates emission and dispersion of primary $PM_{2.5}$ and the resulting concentration in each receptor.[4]

Pollution from each source is emitted at the center of the grid square and dispersed across the region as nonreactive emissions according to a Gaussian-Plume dis-

4. We consider only the impact of primary $PM_{2.5}$ on total $PM_{2.5}$ concentrations. Several other pollutants contribute to total $PM_{2.5}$ concentrations, but these are excluded for simplicity.

persion model. The wind is uniform across the region and travels in many directions weighted by a representative wind rose. The pollution is assumed to be emitted from a point source with the same effective height for each grid square. The Gaussian-Plume dispersion model describes the change in average annual ground level concentration (in μg m^{-3}) at any other grid square resulting from the emission of an additional unit of pollution (tons/year) from a given grid square. Dispersion is calculated for all N grid squares to derive a source-receptor (S-R) matrix that describes the change in concentration at every grid square from the emission of a pollutant from every grid square. Let π_{ji} be the S-R coefficient from source grid square j to receptor grid square i, and let $\Pi_{N\times N}$ denote the S-R matrix for all grid squares.

The concentration of $PM_{2.5}$ is calculated for each grid square based on the emission rates from all squares, $\mathbf{e}$ (an $N \times 1$ vector), the S-R matrix, and a background concentration level, $\tilde{C}$, that accounts for emissions upwind of the modeling domain. Background concentrations, which are constant across the region, are added to the pollution emitted inside the region. In the initial situation, prior to pollution regulation, the concentration in receptor square i is $C_i(\mathbf{e}^0) = \tilde{C} + \sum_{j=1}^{N} \pi_{ji} e_j^0$. After an abatement policy is adopted that induces abatement of $\mathbf{a}$ tons, the level of emissions is $\mathbf{e} = \mathbf{e}^0 - \mathbf{a}$, and the resulting concentration in receptor square i is $C_i(\mathbf{e}) = \tilde{C} + \sum_{j=1}^{N} \pi_{ji} e_j = \tilde{C} + \sum_{j=1}^{N} \pi_{ji}(e_j^0 - a_j)$.

1.1. Krewski et al. Concentration-Response Relationships

Concentration-response functions identify the relative risk of disease given exposure to concentrations of a stressor compared to some baseline. Suppose that the C-R relationship between exposure to fine particulates and adult mortality follows either the log-linear or the log-log functional form reported in Krewski et al. (2009), which are only two of many possible forms the relationship between $PM_{2.5}$ concentrations and risk of mortality can take. By focusing attention on the two forms in Krewski et al. we do not suggest that alternate forms are impossible. Rather we attempt to call attention to the divergent policy implications from these two functional forms, highlighting the importance of identifying the true shape of the C-R function.

We apply the log-linear and log-log C-R functions across the entire range of ambient $PM_{2.5}$ concentrations considered in this model. Because the data are sparse, Krewski et al. is silent on the shape of the relationship at even lower concentrations. It is possible that the function becomes convex in that region. There appears to be little doubt, though, that the function bends downward at very high concentrations (Pope et al. 2009; Smith and Peel 2010).

Krewski et al. report the results of estimating two forms of a hazard function, denoted by $\lambda(\cdot)$, using a random-effects Cox proportional-hazard model. These hazard functions map a given level of concentration, and several covariates, onto the risk of developing a negative health outcome. Taking the ratio of a hazard function evaluated at two different concentration levels results in a hazard ratio (HR). The

HR is reported in table 11 of Krewski et al. For a certain location, or receptor, the HRs identify the relative risk of mortality between a relatively high concentration of pollution and a low concentration. The HR allows us to evaluate, for each receptor, the impact of a change in air pollution concentrations.

To understand the difference between the log-linear and log-log HRs it is necessary to examine the hazard functions (or log-hazard functions, as demonstrated in [1] and [2] below) that were estimated by Krewski et al. The log-linear specification, which we will often refer to as the "lin" form, is given by

$$\ln(\lambda^{\text{lin}}(\mathbf{X}, \text{PM}_{2.5})) = \ln(\hat{\lambda}) + \mathbf{X}\beta^{\text{lin}} + \text{PM}_{2.5}\gamma^{\text{lin}}. \tag{1}$$

The log-log specification, which we will often refer to as the "log" form, is given by

$$\ln(\lambda^{\log}(\mathbf{X}, \text{PM}_{2.5})) = \ln(\hat{\lambda}) + \mathbf{X}\beta^{\log} + \ln(\text{PM}_{2.5})\gamma^{\log}. \tag{2}$$

In (1) and (2), $\hat{\lambda}$ is the baseline risk of disease; $\mathbf{X}$ is a matrix of covariates that affect the risk of disease, with β the estimated effect of these variables; and $\text{PM}_{2.5}$ is the concentration of $\text{PM}_{2.5}$, with γ the estimated effect of $\text{PM}_{2.5}$ concentration. Our interest centers on γ. Note that the log-linear specification (1) regresses the natural log of the risk, or hazard, on the "linear" concentration of fine particulates, whereas the log-log form (2) regresses the natural log of the risk on the natural log of the concentration.

The HR is defined as the ratio of the hazard function evaluated at two values of $\text{PM}_{2.5}$ concentration, $\text{PM}''_{2.5}$ and $\text{PM}'_{2.5}$. This equation is calculated by taking the ratio of the antilog of the log-hazard function at two $\text{PM}_{2.5}$ concentrations. The log-linear and log-log hazard ratios are given by

$$\text{HR}^{\text{lin}} = \frac{\lambda^{\text{lin}}(\mathbf{X}, \text{PM}''_{2.5})}{\lambda^{\text{lin}}(\mathbf{X}, \text{PM}'_{2.5})} = \frac{\hat{\lambda} \cdot \exp\{\mathbf{X}\beta^{\text{lin}} + \text{PM}''_{2.5}\gamma^{\text{lin}}\}}{\hat{\lambda} \cdot \exp\{\mathbf{X}\beta^{\text{lin}} + \text{PM}'_{2.5}\gamma^{\text{lin}}\}} = \exp\{\gamma^{\text{lin}}(\text{PM}''_{2.5} - \text{PM}'_{2.5})\} \tag{3}$$

and

$$\text{HR}^{\log} = \frac{\lambda^{\log}(\mathbf{X}, \text{PM}''_{2.5})}{\lambda^{\log}(\mathbf{X}, \text{PM}'_{2.5})} = \frac{\hat{\lambda} \cdot \exp\{\mathbf{X}\beta^{\log}\}(\text{PM}''_{2.5})^{\gamma^{\log}}}{\hat{\lambda} \cdot \exp\{\mathbf{X}\beta^{\log}\}(\text{PM}'_{2.5})^{\gamma^{\log}}} = \left(\frac{\text{PM}''_{2.5}}{\text{PM}'_{2.5}}\right)^{\gamma^{\log}}. \tag{4}$$

With the HR, taking the ratio of the hazard function at two concentration levels causes all the variables in $\mathbf{X}$ to cancel out, leaving an expression comparing the risks of disease that depends only on the pollution concentration. Solving for γ in (3) and (4) yields

$$\gamma^{\text{lin}} = \frac{\ln(\text{HR}^{\text{lin}})}{\text{PM}''_{2.5} - \text{PM}'_{2.5}}$$

and

$$\gamma^{\log} = \frac{\ln(\text{HR}^{\log})}{\ln(\text{PM}''_{2.5}) - \ln(\text{PM}'_{2.5})}.$$

The hazard ratios reported in table 11 of Krewski et al. are based on a 10 μg m^{-3} difference in fine particulate concentration. Note that for the log-linear form any 10 μg m^{-3} change will lead to the same value of the HR regardless of the baseline level of the concentration. With the log-log form, the value of the HR will change depending on the levels of the concentration. HRs reported in table 11 of Krewski et al. are

$$\mathrm{HR}^{\mathrm{lin}} = 1.060 \text{ for any } 10\mu\text{g m}^{-3} \text{ change}$$

$$\mathrm{HR}^{\log} = \begin{cases} 1.095 \text{ for a } 10\mu\text{g m}^{-3} \text{ change from } 5\mu\text{g m}^{-3} \text{ to } 15\mu\text{g m}^{-3} \\ 1.059 \text{ for a } 10\mu\text{g m}^{-3} \text{ change from } 10\mu\text{g m}^{-3} \text{ to } 20\mu\text{g m}^{-3} \end{cases}.$$

The estimated values of γ, then, are

$$\gamma^{\mathrm{lin}} = \frac{\ln(1.060)}{10} = 0.005827 \tag{5}$$

and

$$\gamma^{\log} = \frac{\ln(1.059)}{\ln(20) - \ln(10)} = 0.082703. \tag{6}$$

Using these values of γ, we can construct an HR for any $PM_{2.5}$ concentration compared to an initial baseline concentration. We will define the baseline concentration in receptor i as the concentration at the initial level of emissions, $\mathrm{PM}''_{2.5} = \mathrm{C}_i(\mathbf{e}^0)$. The concentration in receptor i for some other level of emissions, $\mathbf{e}$, is defined as $\mathrm{PM}'_{2.5} = \mathrm{C}_i(\mathbf{e})$. The HRs in receptor i become[5]

$$\mathrm{HR}_i^{\mathrm{lin}}(\mathrm{C}_i(\mathbf{e})) = \exp\{\gamma^{\mathrm{lin}}(\mathrm{C}_i(\mathbf{e}^0) - \mathrm{C}_i(\mathbf{e}))\} \tag{7}$$

and

$$\mathrm{HR}_i^{\log}(\mathrm{C}_i(\mathbf{e})) = \left(\frac{\mathrm{C}_i(\mathbf{e}^0)}{\mathrm{C}_i(\mathbf{e})}\right)^{\gamma^{\log}}. \tag{8}$$

1.2. Benefits of Abatement

To calculate the benefits of pollution abatement in receptor i we first go back to the original definition of the HR in (3) and (4), the ratio of hazard functions, $\lambda_i(\cdot)$:

$$\mathrm{HR}_i(\mathrm{C}_i(\mathbf{e})) = \frac{\lambda_i^0}{\lambda_i(\mathrm{C}_i(\mathbf{e}))}. \tag{9}$$

5. Note that the initial concentration is not an argument of the HR function because it is fixed under all abatement policies.

In (9), $\lambda_i^0 = \lambda_i(C_i(\mathbf{e}^0))$ is defined as the risk of disease given the initial concentration before regulation, and $\lambda_i(C_i(\mathbf{e}))$ is defined as the risk given a lower concentration in receptor i after a reduction in emissions. Rearranging (9), the risk of mortality in receptor i for any level of emissions is $\lambda_i(C_i(\mathbf{e})) = \lambda_i^0/\mathrm{HR}_i(C_i(\mathbf{e}))$.

Assume that premature mortality is the only identified risk from the air pollution. We can estimate the expected number of deaths in receptor i as the receptor's population times the risk of mortality, $\mathrm{Deaths}_i(C_i(\mathbf{e})) = \mathrm{Pop}_i \cdot \lambda_i^0/\mathrm{HR}_i(C_i(\mathbf{e}))$. The change in deaths in receptor i after a reduction in emissions from $\mathbf{e}^0$ to $\mathbf{e}$ is $\Delta\mathrm{Deaths}_i(C_i(\mathbf{e})) = \mathrm{Pop}_i \cdot \lambda_i^0[1 - 1/\mathrm{HR}_i(C_i(\mathbf{e}))]$. Next we define the vector of emissions in all sources after regulation in terms of the vector of abatement from all sources, $\mathbf{e} = \mathbf{e}^0 - \mathbf{a}$. This way we can write the change in expected deaths and the concentration level after regulation as a function of a vector of abatement.[6]

Define $\mathcal{V}$ as the value society places on each human life. Therefore, the benefits in receptor i of a vector of abatement in all sources are the changes in expected deaths times the value of a life saved.

$$\mathrm{B}_i(C_i(\mathbf{e}^0 - \mathbf{a})) = \mathcal{V} \cdot \Delta\mathrm{Deaths}_i(C_i(\mathbf{e}^0 - \mathbf{a})) = \mathcal{V} \cdot \mathrm{Pop}_i \cdot \lambda_i^0 \left[1 - \frac{1}{\mathrm{HR}_i(C_i(\mathbf{e}^0 - \mathbf{a}))}\right]. \quad (10)$$

These benefits are the difference in monetized health damages without and with regulation, defined as a function of the hazard ratio. This implies that the benefits for receptor i from the two C-R functions in (7) and (8) are

$$\mathrm{B}_i^{\mathrm{lin}}(C_i(\mathbf{e}^0 - \mathbf{a})) = \mathcal{V} \cdot \mathrm{Pop}_i \cdot \lambda_i^0[1 - \exp\{-\gamma^{\mathrm{lin}}(C_i(\mathbf{e}^0) - C_i(\mathbf{e}^0 - \mathbf{a}))\}]$$

and

$$\mathrm{B}_i^{\log}(C_i(\mathbf{e}^0 - \mathbf{a})) = \mathcal{V} \cdot \mathrm{Pop}_i \cdot \lambda_i^0 \left[1 - \left(\frac{C_i(\mathbf{e}^0 - \mathbf{a})}{C_i(\mathbf{e}^0)}\right)^{\gamma^{\log}}\right].$$

The total benefits for all receptors in the region, resulting from abatement, $\mathbf{a}$, from all sources, are the sum of the benefits across receptors.

$$\mathrm{B}^{\mathrm{lin}}(\mathbf{a}) = \sum_{i=1}^{N} \mathrm{B}_i^{\mathrm{lin}}(C_i(\mathbf{e}^0 - \mathbf{a}))$$

and

$$\mathrm{B}^{\log}(\mathbf{a}) = \sum_{i=1}^{N} \mathrm{B}_i^{\log}(C_i(\mathbf{e}^0 - \mathbf{a})).$$

The total benefits are the value of risk reductions in all receptors resulting from a vector of abatement, $\mathbf{a}$, at every source of pollution. Next we investigate how the ben-

6. We write $C_i(\mathbf{e}) = C_i(\mathbf{e}^0 - \mathbf{a})$ to indicate that the concentration in a receptor is a function of the level of abatement.

efits in all receptors change from an incremental change in abatement at any single source.

1.3. Interrelated Marginal Benefits across Sources

With the total benefits in all receptors we can examine the marginal benefits of additional abatement from source j. We start with the marginal benefits in receptor i associated with a change in concentration in i (suppressing the argument of C_i):

$$\mathrm{MB}_i(\mathrm{C}_i) = \frac{\partial \mathrm{B}_i(\mathrm{C}_i)}{\partial \mathrm{C}_i} = \frac{\mathcal{V}\mathrm{Pop}_i\lambda_i^0}{[\mathrm{HR}_i(\mathrm{C}_i)]^2}\frac{\partial \mathrm{HR}_i(\mathrm{C}_i)}{\partial \mathrm{C}_i}.$$

The marginal benefits in receptor i attributable to a change in abatement at source j is just $\mathrm{MB}_i(\mathrm{C}_i)$ times π_{ji}, the incremental impact on concentrations in i from emissions at j. Summing across all receptors, we obtain the combined marginal benefits of additional abatement from source j:

$$\mathrm{MB}_j(\mathbf{a}) = \sum_{i=1}^{N} \mathrm{MB}_i(\mathrm{C}_i(\mathbf{e}^0 - \mathbf{a}))\pi_{ji}.$$

The marginal benefits of abatement from source j are the sum of the change in benefits in all downwind receptors from an incremental increase in abatement at that source. For the log-linear and log-log C-R functions the expressions for the marginal benefits of abatement from source j are given by

$$\mathrm{MB}_j^{\mathrm{lin}}(\mathbf{a}) = \mathcal{V}\gamma^{\mathrm{lin}} \sum_{i=1}^{N} \frac{\mathrm{Pop}_i\lambda_i^0\pi_{ji}}{\mathrm{HR}_i^{\mathrm{lin}}(\mathrm{C}_i(\mathbf{e}^0 - \mathbf{a}))}$$

and

$$\mathrm{MB}_j^{\log}(\mathbf{a}) = \mathcal{V}\gamma^{\log} \sum_{i=1}^{N} \frac{\mathrm{Pop}_i\lambda_i^0\pi_{ji}}{\mathrm{C}_i(\mathbf{e}^0 - \mathbf{a}) \cdot \mathrm{HR}_i^{\log}(\mathrm{C}_i(\mathbf{e}^0 - \mathbf{a}))}.$$

The marginal benefits of abatement, or equivalently the marginal damages of emissions, are different for most or possibly all sources, as demonstrated in Muller and Mendelsohn (2009), and NRC (2010). Muller and Mendelsohn (2009) report median marginal damages across US counties of \$1,170 (2000 US dollars) per ton of primary $PM_{2.5}$, with a range of \$41,000 between the 1st and 99.9th percentiles. In a report by the National Research Council (NRC 2010) median marginal damages across coal power plants are estimated at \$7,100 (2007 US dollars) per ton of primary $PM_{2.5}$, with a range of \$23,400 between the 5th and 95th percentiles.[7]

7. Muller and Mendelsohn (2009) and the NRC report (2010) use the log-linear C-R function from Pope et al. (2002). Krewski et al. (2009) is an update of Pope et al. (2002).

The heterogeneity of marginal benefits of abatement across sources is heavily influenced by the size of the population near the source.[8] The marginal benefits with the log-log C-R function (but not with the log-linear C-R function) will also be substantially influenced by the $PM_{2.5}$ concentration of the receptor grid squares near the source. A source emitting pollution near receptors with low pollution concentrations will have higher marginal benefits of abatement than a source near high concentration receptors (given equal receptor populations) because of the concavity of the log-log C-R function. However, the lowest concentration receptors are also likely to have the lowest population density. If the log-log C-R function is correct, these two effects, higher population in dirtier places and greater risk reductions in cleaner places, pull in opposite directions. The overall effect might be to reduce the variance of the distribution of marginal benefits of abatement with log-log compared to log-linear.

The marginal benefits in source j are a function of the level of abatement from all sources of the pollution. The interconnected nature of the marginal benefit functions across sources turns out to be quite important. How do the marginal benefits of abatement from source j change when source k increases its abatement? The relevant effects are

$$\frac{\partial \mathrm{MB}_j^{\mathrm{lin}}(\mathbf{a})}{\partial a_k} = -\mathcal{V}(\gamma^{\mathrm{lin}})^2 \sum_{i=1}^{N} \frac{\mathrm{Pop}_i \lambda_i^0 \pi_{ji} \pi_{ki}}{\mathrm{HR}_i^{\mathrm{lin}}(\mathrm{C}_i(\mathbf{e}^0 - \mathbf{a}))} \tag{11}$$

and

$$\frac{\partial \mathrm{MB}_j^{\mathrm{log}}(\mathbf{a})}{\partial a_k} = -\mathcal{V}\gamma^{\mathrm{log}}(\gamma^{\mathrm{log}} - 1) \sum_{i=1}^{N} \frac{\mathrm{Pop}_i \lambda_i^0 \pi_{ji} \pi_{ki}}{[\mathrm{C}_i(\mathbf{e}^0 - \mathbf{a})]^2 \mathrm{HR}_i^{\mathrm{log}}(\mathrm{C}_i(\mathbf{e}^0 - \mathbf{a}))}, \tag{12}$$

for the log-linear and log-log C-R, respectively. Using the specific parameter values for γ found in (5) and (6), we can determine the sign of equations (11) and (12). Note that the parameters are all positive, and most importantly for equation (12), $\gamma^{\mathrm{log}} < 1$. This means that, although equation (11) is negative, the $(\gamma^{\mathrm{log}} - 1)$ term guarantees that equation (12) is positive. When $k = j$ it is clear that the marginal benefit function for source j is decreasing in abatement a_j for log-linear, but increasing in a_j for log-log.

When $j \neq k$ with the log-linear C-R equation, the marginal benefits of abatement from source j are decreasing with abatement from source k. Therefore, abatement from different sources can be considered substitutes: additional abatement from one source decreases the marginal benefits of abatement from other sources. With the log-log C-R function, on the other hand, the marginal benefits of abatement from

8. Marginal benefits of abatement are closely linked with the relationship between emissions and human intake, known as the intake fraction (see Bennett et al. 2002). Larger populations near sources are associated with a greater intake fraction.

source j are increasing with abatement from source k. Thus, abatement levels across sources are complements.

Two questions arise from this differential feature of the two specifications. First, which of the two effects (substitute for log-linear or complement for log-log) is larger? And second, are either of these effects significantly different from zero? To answer the first question, consider the ratio of these two expressions:

$$\Lambda = \frac{\frac{\partial MB_j^{\log}(\mathbf{a})}{\partial a_k}}{\frac{\partial MB_j^{\text{lin}}(\mathbf{a})}{\partial a_k}} = \frac{\gamma^{\log}(\gamma^{\log}-1)}{(\gamma^{\text{lin}})^2}\left[\frac{\sum_{i=1}^{N}\text{Pop}_i \cdot \lambda_i^0 \pi_{ji}\pi_{ki} C_i(\mathbf{e}^0)^{-\gamma^{\log}} C_i(\mathbf{e}^0-\mathbf{a})^{\gamma^{\log}-2}}{\sum_{i=1}^{N}\text{Pop}_i \cdot \lambda_i^0 \pi_{ji}\pi_{ki} \cdot \exp\{-\gamma^{\text{lin}}(C_i(\mathbf{e}^0)-C_i(\mathbf{e}^0-\mathbf{a}))\}}\right].$$

For the moment, assume that the concentration level is the same in each receptor i: $C_i(\mathbf{e}^0) = C(\mathbf{e}^0)$ and $C_i(\mathbf{e}^0 - \mathbf{a}) = C(\mathbf{e}^0 - \mathbf{a})$. (This assumption is not appropriate for the rest of our model, but it does help shed light on the characteristics of Λ.) This allows us to cancel out all the Pop, π, and λ^0 terms, leaving

$$\Lambda = \frac{\gamma^{\log}(\gamma^{\log}-1)}{(\gamma^{\text{lin}})^2}\frac{C(\mathbf{e}^0)^{-\gamma^{\log}} C(\mathbf{e}^0-\mathbf{a})^{\gamma^{\log}-2}}{\exp\{-\gamma^{\text{lin}}(C(\mathbf{e}^0)-C(\mathbf{e}^0-\mathbf{a}))\}}.$$

Plugging in the parameter values found in (5) and (6) and using concentration levels commonly found in the United States, the absolute value of Λ can range from 10 to 60, with the largest values at low concentrations. This finding suggests that the complement effect in the log-log function is far more important than the substitution effect in the log-linear function, and at lower concentrations the difference is even more pronounced. A large complement effect suggests that for multiple sources that are interrelated (such that their pollution affects common receptors), emission reductions from one source would increase the marginal benefits of abatement from the other sources. The incremental gains, in terms of reductions in risk, at the impacted receptors from additional abatement are larger after one source has reduced emissions. This outcome is embodied by the concave shape of the log-log C-R function in figure 1, where the steepest part of the curve is found at the lowest concentration levels. Achieving low concentrations in receptors allows for the largest reductions in risk of mortality, per unit of concentration reduction.

The second question is whether the complement effect is large in absolute value, rather than just in relation to the substitution effect. This question is an empirical matter, but results given below indicate that the complement effect contributes to a preference for lower emissions and lower concentrations with the log-log C-R function than with log-linear.

1.4. Costs of Abatement

The primary focus of this paper is the impact of the functional form of the C-R function on the benefits of pollution abatement. However, to provide an interesting analysis of pollution abatement policies it is necessary to specify the costs of abatement. The cost of abatement at each source is assumed to be independent of the other sources. The form of the marginal cost function (below) was chosen to have a relatively flat slope for the first units of abatement and a steeper slope as abatement increases, indicating that abatement becomes exceedingly expensive as a source attempts to completely eliminate their pollution. The marginal cost functional is strictly convex in a_j and is defined as

$$\mathrm{MC}_j(a_j) = \phi_{1j} - \phi_{2j} \cdot \ln\left(1 - \frac{a_j}{e_j^0}\right),$$

with $\phi_{1j} \geq 0$ and $\phi_{2j} > 0$. As seen in figure 2, the marginal costs rise to infinity as abatement approaches the maximum $(\lim_{a_j \to e_j^0} \mathrm{MC}_j(a_j) = \infty)$.

In the simulations, described in section 2, marginal costs are heterogeneous across sources. This outcome is accomplished by randomly assigning values for parameters ϕ_{1j} and ϕ_{2j} for each source. The simulation assumes an initial situation with no pollution regulation, and then various policies to regulate pollution are introduced. The parameter values are calibrated to make the simulation economically interesting. That is, we ensure that marginal costs are small enough to induce abatement and large enough to discourage nearly complete abatement. Although the cost parameters are randomly assigned to sources in the initial situation, after abatement policies have been implemented the largest marginal costs are found, on average, at sources that had the greatest amount of abatement.

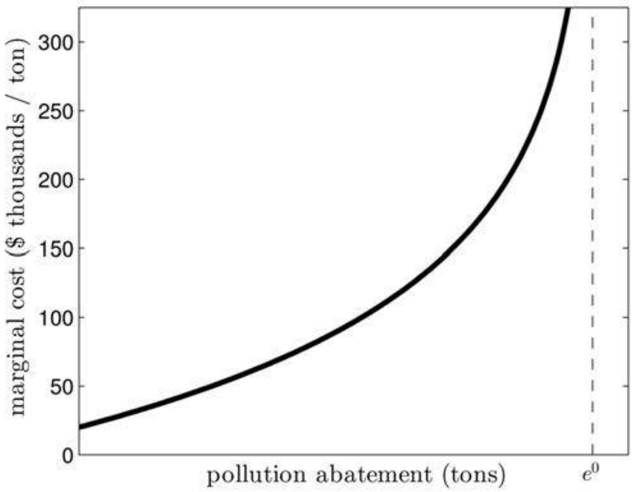

Figure 2. Illustration of marginal cost of abatement curve from zero abatement to complete abatement (e^0).

The corresponding abatement cost function with fixed costs F is

$$\mathrm{Cost}_j(a_j) = \left(\phi_{1j} + \phi_{2j}\right)a_j + \phi_{2j}\left(e_j^0 - a_j\right)\ln\left(1 - \frac{a_j}{e_j^0}\right) + F.$$

The total cost of a vector of abatement levels is the sum of the costs for individual sources:

$$\mathrm{Cost}(\mathbf{a}) = \sum_{j=1}^{N} \mathrm{Cost}_j(a_j).$$

1.5. Abatement Policies

With the benefits and costs of pollution abatement established for each receptor and source in the region, we examine three approaches to abatement. The first approach (called "efficient abatement") selects abatement levels at each source to maximize the difference between the benefits and costs of abatement. The second approach is a uniform pollution concentration standard across the region, designed to emulate the NAAQS, achieved through a command-and-control approach. The third approach is a uniform tax on emissions. The uniform tax yields a cost-effective outcome but ignores the spatial heterogeneity of marginal damages of emissions among sources. The difference in the outcomes between efficient abatement and the uniform tax identifies the importance of implementing source-specific regulation. All three approaches (policies) are considered with the log-linear and log-log C-R functions.

Efficient abatement can be represented for the log-linear C-R function, as

$$\begin{aligned} &\max_{\mathbf{a}} \left\{\mathrm{B}^{\mathrm{lin}}(\mathbf{a}) - \mathrm{Cost}(\mathbf{a})\right\} \\ &\text{Subject to: } a_j \geq 0,\ a_j \leq e_j^0 \text{ for } j = 1, \ldots, N, \end{aligned} \tag{13}$$

and, for the log-log C-R function, as

$$\begin{aligned} &\max_{\mathbf{a}} \left\{\mathrm{B}^{\mathrm{log}}(\mathbf{a}) - \mathrm{Cost}(\mathbf{a})\right\} \\ &\text{Subject to: } a_j \geq 0,\ a_j \leq e_j^0 \text{ for } j = 1, \ldots, N. \end{aligned} \tag{14}$$

No source completely eliminates its pollution, because the slope of the marginal cost curve approaches infinity as abatement approaches e^0, but zero abatement is possible for some sources if the costs of abatement are high. The first-order conditions, then, are different depending on whether this corner comes into play:

$$\mathrm{MB}_j(\mathbf{a}) = \begin{cases} \mathrm{MC}_j(a_j) & \text{if } a_j > 0 \\ \mathrm{MC}_j(0) - \mu_j & \text{if } a_j = 0 \end{cases},$$

where the μ_j are the Lagrange multipliers on the zero abatement constraints. The N marginal benefit functions are interdependent, as abatement at each source affects the marginal benefits at all other sources. As the number of sources becomes large, these problems pose computational challenges because of the number of equations that must be solved simultaneously.[9]

In the second policy, the uniform standard selects a concentration limit, $\overline{C}$, that cannot be exceeded in any location. The optimal concentration limit is computed by setting a concentration limit, imposing emission reductions at sources to satisfy the limit, and calculating the benefits and costs of abatement. This approach is repeated for a series of limits at progressively stricter levels (lower concentrations). The uniform standard adopted (one standard for the whole region) is the concentration limit that achieves the greatest net increase in welfare for society. This concentration is referred to as the "best" uniform standard for the region.

Under this command-and-control policy, in order to achieve any given concentration limit, emission reductions are determined based on that receptor, among all those to which the source contributes measurably, that has the highest concentration. To avoid constraining distant sources that have a minimal impact on an out-of-compliance receptor, here we defined a source as contributing pollution to a receptor if the relevant entry in the S-R matrix is above a lower threshold, ε.[10] We define θ_{ji} as an indicator variable that equals one if $\pi_{ji} \geq \varepsilon$ and zero if $\pi_{ji} < \varepsilon$. We employ the following approach for determining emission reductions: for each source j the emissions required to comply with the concentration limit are equal to the ratio of the proposed limit, $\overline{C}$, and the maximum concentration in a receptor to which source j contributes pollution, denoted $\mathcal{C}_j$. If $\mathcal{C}_j$ is less than the proposed limit, emissions remain at the status quo, e_j^0. This maximum concentration that a source contributes pollution is defined as $\mathcal{C}_j = \max\{C_1 \cdot \theta_{j1}, \ldots, C_N \cdot \theta_{jN}\}$. The approach does not optimize abatement by minimizing the costs of emission reductions. Rather, each source reduces emissions by the proportion of its contribution to any downwind receptor that is out of compliance with the concentration limit.

For the log-linear functional form the problem is formally stated as

$$\begin{aligned} &\max_{\overline{C}}\{B^{\text{lin}}(\mathbf{a}) - \text{Cost}(\mathbf{a})\} \\ &\text{Subject to: } a_j = e_j^0 \cdot \min\left\{1, 1 - \frac{\overline{C}}{\mathcal{C}_j}\right\} \text{ for } j = 1, \ldots, N, \end{aligned} \tag{15}$$

9. With the log-log C-R function there is the possibility of a nonconvexity because the marginal benefit and marginal cost curves are both increasing in abatement. In this model the potential for a nonconvexity is very small because the absolute value of the slope of the marginal cost curve is likely greater than the absolute value of the slope of the marginal benefit curve in own-source abatement.

10. $\varepsilon = 1.0 \times 10^{-6}$. For entries in the S-R matrix greater than this value of ε suggests that for each additional ton of emissions from a source, the annual concentration in the receptor is increased by more than 1 millionth of a μg m^{-3}.

and for the log-log functional form as

$$\max_{\overline{C}}\{B^{\log}(\mathbf{a}) - \text{Cost}(\mathbf{a})\}$$
$$\text{Subject to: } a_j = e_j^0 \cdot \min\left\{1, 1 - \frac{\overline{C}}{C_j}\right\} \text{ for } j = 1, \ldots, N. \tag{16}$$

The regional concentration standards (the NAAQS values calculated here) will depend on the C-R function because the benefits of abatement are determined by the functional form of the HR.

The third policy is a uniform tax where the regulator must choose a single tax rate on emissions to maximize the difference between total benefits of abatement and total costs of abatement. For each source the resulting quantity of abatement from any chosen tax policy is the greater of zero and the intersection of the tax and the source's marginal cost curve. For the log-linear C-R function the problem is stated as

$$\max_{t}\{B^{\text{lin}}(\mathbf{a}) - \text{Cost}(\mathbf{a})\}$$
$$\text{Subject to: } a_j = \max\left\{0, MC_j^{-1}(t)\right\} \text{ for } j = 1, \ldots, N, \tag{17}$$

and for the log-log functional form as

$$\max_{t}\{B^{\log}(\mathbf{a}) - \text{Cost}(\mathbf{a})\}$$
$$\text{Subject to: } a_j = \max\left\{0, MC_j^{-1}(t)\right\} \text{ for } j = 1, \ldots, N. \tag{18}$$

2. MODEL SOLUTION AND RESULTS

The model analyzes a hypothetical geographical region that is 750 km east/west and 500 km north/south (an area approximately 5% the size of the contiguous United States). The region is separated into 25 km × 25 km grid squares, with a total of $N = 600$ grid squares that are each a source and receptor of air pollution. The populations of the grid squares in the region are modeled after a section of the US Midwest that spans from northwest West Virginia to southeast Wisconsin.[11] The emissions from each grid square prior to regulation are artificially determined but are correlated with that grid square's population, with a correlation coefficient $\rho = 0.44$.[12] The model and this example are meant to be representative of a generic situation of

11. The parameters of the dispersion model and the emissions from sources are artificial and not calibrated to the modeled geographic region. Modeled concentrations are not meant to mirror observed concentrations in this region.

12. The correlation coefficient is derived from the correlation between criteria pollutant emissions and population from counties in Illinois, Indiana, Michigan, and Ohio.

air pollution and how abatement policies will affect the welfare of the region. Mapping the actual population of a region of the Midwest and correlating the emissions with population is done to provide a reasonable reflection of a real-world situation.[13]

2.1. Model Solution

The model assumes an initial situation without pollution regulation. The model then solves for three abatement policies: efficient abatement, a uniform pollution concentration standard across the region, and a uniform emissions tax. Each policy is analyzed with both of the Krewski et al. (2009) C-R functions: log-linear and log-log.

The model is run 1,000 times with different abatement cost parameter values and distributions of initial emissions at the sources, randomly selected, to provide a wide array of possible outcomes. The total quantity of emissions, prior to regulation, across the region is fixed in each iteration, but the allocation of initial emissions to each grid square is randomly assigned, with the approximate correlation between emissions and population maintained. The marginal cost parameters for each grid square source are randomly drawn from distributions in each model run.[14]

In the efficient abatement policy, which solves the maximization problems in (13) and (14), emissions are selected to maximize the difference between the benefits to society of reduced mortality and the costs of abatement for polluters. Solving this problem presents significant computational challenges, requiring as it does the simultaneous solution of $N = 600$ equations and 600 unknowns. We adopted an iterative numerical approach that yields the optimum in a computationally efficient manner.[15] The iterative method is based upon the algorithm suggested by Antweiler (2012),

13. Our input parameters for the Gaussian-Plume dispersion model include a constant ground level wind speed of 5.24 m/sec, based on the average annual wind speed in Minnesota at a height of 10 m, with a west to east prevailing direction. The emissions from each grid square are assumed to be emitted from a point source with an effective height of 250 m. The background concentration level of $PM_{2.5}$ is $\tilde{C} = 4\mu g\,m^{-3}$. Following US Environmental Protection Agency recommendations (EPA 2010) regarding the value of a statistical life (VSL), the parameter $\mathcal{V}$ is equal to \$8.43 million (2012 US dollars). The baseline risk of mortality, λ_i^0, is assumed to be the same in each receptor, and is set to the 2011 national mortality rate of 806.6 deaths per 100,000 population (Hoyert and Xu 2012).

14. The parameters ϕ_1 and ϕ_2 for each source are both independently drawn from normal distributions: $\phi_1 \sim \mathcal{N}(20{,}000, 8{,}000)$; $\phi_2 \sim \mathcal{N}(100{,}000, 50{,}000)$. Draws from the ϕ_1 distribution that are negative values are assigned a value of zero, and draws from the ϕ_2 distribution that are nonpositive are assigned a value of 10. Fixed costs are assumed to be zero for all sources, $F = 0$.

15. We confirmed this claim by solving an otherwise identical model, but with 150 grid squares instead of 600. At $N = 150$ it is just possible to compute the solution directly using a personal computer. We compared the efficient iterative solution to the fully simultaneous

who envisions an environmental regulator who selects a set of source-specific discriminating taxes in each period, adjusting the taxes in response to the observed emissions decisions by sources. In each period (which is best interpreted as an iteration in our algorithm), the taxes are set equal to each source's marginal benefits of abatement, computed at the previous period's abatement level. Then the abatement level for the next iteration is determined by equating marginal benefits and marginal costs for each source (taking into account possible corner solutions). Because marginal benefits are based on abatement levels in the previous iteration, the simultaneous equation problem is avoided. In the first step, the abatement levels are not optimal, but after several iterations the solution converges to the optimum found by solving the equations simultaneously. With the large number of sources in the model, and the 1,000 model runs with different parameter values, the iterative solution method is computationally efficient and very accurate.

2.2. Model Results

Across the 1,000 runs of the model, substantial differences appear between the outcomes from the log-linear and log-log C-R functions. With an efficient abatement policy, if the true C-R function is log-log, society should prefer fewer emissions, lower average concentrations of fine particulates, and therefore, lower risks of mortality, than if the true C-R function is log-linear. This finding is attributable to the comparatively large reductions in risk of mortality that are possible from obtaining low concentrations of fine particulates with a log-log C-R function. This result highlights the importance of discovering the true shape of the C-R function between adult mortality and fine particulate exposure as the preferred abatement policies and outcomes are substantially different.

2.2.1. Efficient Policy and Uniform Pollution Standard

The results show that when abatement costs are sufficiently large an efficient abatement policy is usually preferred to a uniform pollution standard for fine particulate concentrations. This preference exists for both C-R functions and suggests that policies directed at obtaining the greatest risk reductions at the lowest cost may provide enough benefits to outweigh the environmental justice concerns of not primarily focusing emission reductions at the dirtiest locations.

The following results report the outcomes from the median of the 1,000 model runs. We analyze and compare the outcomes of the model from two of the policies examined: efficient abatement policy with log-linear and log-log C-R functions and

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solution for a sample of 20 randomly selected runs. The numerical error between the two methods was very small: 0.002% with the log-linear C-R function and 0.001% with log-log.

the "best" uniform pollution standard with log-linear and log-log C-R functions. Prior to regulation, there are 3.22×10^6 tons of emissions across the region. With the efficient abatement policy, across the 1,000 runs, the median emission reduction is 22% and 38% with log-linear and log-log C-R functions, respectively. With the uniform standards, emissions are reduced by 18% (log-linear C-R) and 30% (log-log). For both policies, total emissions and population-weighted average concentrations are lower for the log-log than for the log-linear C-R function. The largest population-weighted average concentration reduction is achieved by the efficient abatement policy with the log-log C-R function. From an initial population-weighted average concentration of 12.2 μg m^{-3}, the efficient abatement policy leads to a population-weighted average concentration of 10.0 μg m^{-3} for log-linear, and 8.6 μg m^{-3} for log-log. The "best" uniform standards yield population-weighted average concentrations of 10.8 μg m^{-3} (log-linear) and 9.7 μg m^{-3} (log-log).

With the efficient abatement policy, concentration reductions (2.2 μg m^{-3} [log-linear] and 3.6 μg m^{-3} [log-log]) would reduce annual expected deaths across the region by 4,000 with log-linear versus 8,950 for log-log. The lower expected mortality with log-log is attributable to both the lower average concentrations and the comparatively smaller risks at low concentrations with this C-R function. The amount of abatement (and therefore in our model the total costs of abatement) is higher for log-log than for log-linear, because greater abatement is justified by the greater reductions in risk of mortality. Under the "best" uniform standards the reduction in expected mortality is 2,700 with log-linear and 5,900 with log-log.

With a log-log C-R function the total emissions from the efficient abatement policy are only 11% less than with the "best" uniform standard; however, the efficient policy is able to achieve a 52% greater reduction in expected mortality across the region compared with the uniform standard. An efficient abatement policy is able to more precisely target abatement to reduce risks of mortality.

The effectiveness of the efficient abatement policies is demonstrated by a comparison of the net benefits of abatement between the two policies and the two C-R functions, which combines the benefits from risk reductions with the costs of abatement for the polluting sources. Figure 3, which displays both the net benefits of abatement and the population-weighted average concentration across the region for all model runs, shows that the efficient abatement policies are able to achieve far greater welfare for society than a uniform standard while also reducing the average concentration to lower levels. The ellipse inside each cluster of points in figure 3 encircles the outcomes within one standard deviation from the mean, in each dimension, of the 1,000 model runs. In the median model run, net benefits with a log-linear C-R function are \$13 billion for the efficient abatement policy and \$5.8 billion for the "best" uniform standard. For the log-log C-R function, net benefits are \$26 billion (efficient policy) and \$13 billion (uniform standard). Under either policy, the net benefits of abatement are much larger if the C-R function is log-log compared to log-linear. If the true C-R

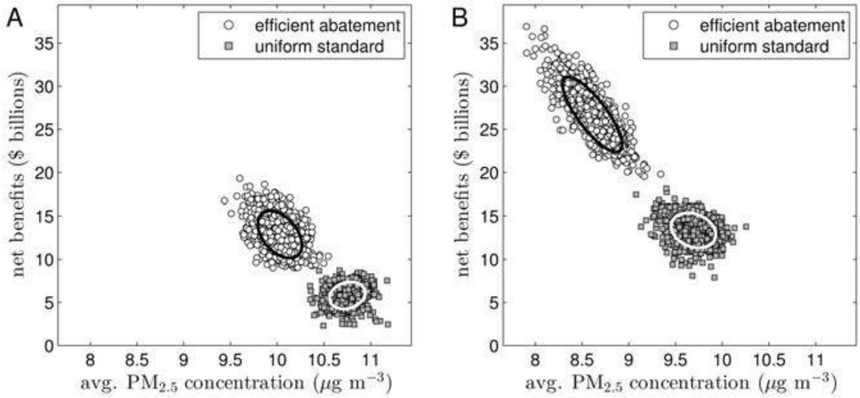

Figure 3. Efficient abatement policy versus uniform standard: net benefits of abatement and population-weighted average pollution concentration for each model run: log-linear C-R function (*A*), log-log C-R function (*B*). The four clusters each contain 1,000 points, of which 69%–71% are encircled by the respective ellipse. Each ellipse radius represents one standard deviation from the mean. The points inside each ellipse are the outcomes nearest the center of the joint distribution of $PM_{2.5}$ concentration and net benefits.

function is identified as log-log, regulators could justify imposing a more restrictive pollution control policy.

Across the 1,000 model runs the distribution of the outcomes is tightly centered around the median, indicating that the median results presented above provide a good representation of the array of outcomes that are possible in the model. This outcome suggests that across many profiles of initial emissions and abatement costs from sources, the general pattern holds that society prefers lower emissions with a log-log than with a log-linear C-R function. This conclusion is demonstrated in figure 4 for total emissions of pollution and population-weighted average concentrations of $PM_{2.5}$ across the region. The distributions of the outcomes across the model runs from the four policies show clearly that emissions and concentrations are lower with the log-log C-R function compared with the log-linear function. There is also a less obvious but clear distinction between the efficient policies and the uniform standards, with lower emissions and concentrations under the efficient policies.

Differences also exist between the maximum allowable concentrations from the "best" uniform standard under the two C-R functional forms. In figure 5, the median standard with the log-linear C-R function is set at 13.25 $\mu g\ m^{-3}$, while the median standard with log-log is more stringent, at 11.75 $\mu g\ m^{-3}$. The primary cause of the lower standard with the log-log C-R function is the greater ancillary benefits that accrue to low-concentration receptors when limiting emissions to meet the standard at the dirtiest receptors. While the standard is designed to limit the pollution in the dirtiest locations, the resulting emission reductions also clean the air in surround-

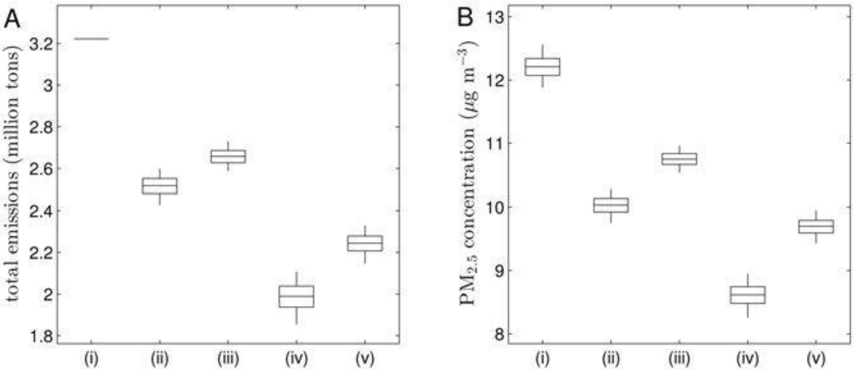

Figure 4. Distribution of outcomes across 1,000 model runs: total emissions across region (*A*), population-weighted average $PM_{2.5}$ concentration across region (*B*): (i) initial situation without regulation, (ii) log-linear efficient abatement policy, (iii) log-linear "best" uniform standard, (iv) log-log efficient abatement policy, (v) log-log "best" uniform standard. Boxplot: center line represents median, top and bottom of box represent 25th and 75th percentiles, and ends of whiskers represent 5th and 95th percentiles. The total emissions boxplot appears as a single line under the initial situation without regulation because it is a constant value in all model runs.

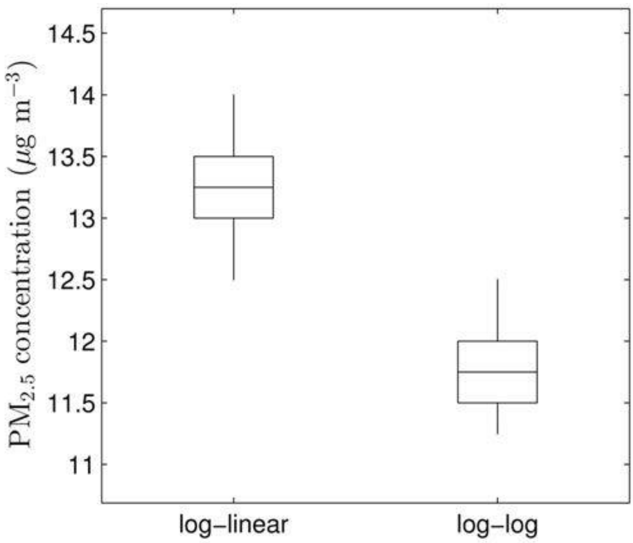

Figure 5. Distribution of maximum allowable $PM_{2.5}$ concentration of "best" uniform standard with log-linear and log-log C-R functions across 1,000 model runs. Boxplot: center line represents median, top and bottom of box represent 25th and 75th percentiles, and ends of whiskers represent 5th and 95th percentiles.

ing (i.e., comparatively cleaner) areas, leading to risk reductions at those cleaner areas. Because of the steep slope of the log-log C-R function at low concentrations, large risk reductions are also achieved in nearby clean receptors. The larger benefits (with log-log compared to log-linear) at the comparatively cleaner receptors offset the greater costs of setting a lower, stricter uniform concentration standard across the region.

In the United States, uniform pollution standards under the NAAQS are used to limit the risks associated with criteria air pollutants. One apparent virtue of these policies is the perceived equity of protecting everyone from the greatest risks from pollution (i.e., the standard is the same everywhere). Under an efficient abatement policy, environmental justice concerns may arise. The focus is on making the greatest risk reductions at the lowest cost, regardless of equity among receptors. Of course, even with uniform standards inequality still exists (Brulle and Pellow 2006; Marshall 2008; Mohai, Pellow, and Roberts 2009; Su et al. 2009; Clark, Millet, and Marshall 2014). In previous studies (Marshall, Zwor, and Nguyen 2014), it was found that more than 90% of articles on environmental justice in the United States reported that air pollution exposures are greater for lower than for higher socioeconomic status groups (e.g., based on income, race, education level, or other attributes). Dockery et al. (1993) reported that there is no threshold of fine particulate concentration below which risks of mortality are nonexistent (see also Pope and Dockery 2006). Receptors with concentrations below the uniform standard face less risk than those receptors that just meet the standard. The question becomes how much inequality is acceptable.

An efficient policy abates sources that would lead to the greatest risk reductions, but surrounding receptors also experience concentration reductions because of pollutant dispersion. Disregarding equity or justice under an efficient abatement policy may initially appear objectionable, but the policy should be evaluated based on a comparison of the realized level of inequality or injustice against the overall welfare gains. Figure 3 demonstrates the substantial advantage of the efficient abatement policies over the uniform standards both with greater net benefits to society and lower average fine particulate concentrations. Surprisingly, the level of inequality, as measured by the Gini coefficient of the differences in fine particulate concentrations across the region, is slightly lower with the efficient policy. With a log-linear C-R relationship the median Gini coefficient across the model runs is 0.077 under the efficient policy and 0.090 under the uniform standard. With log-log the Gini coefficient is 0.060 under the efficient policy and 0.066 under the uniform standard. These differences are small and show significant improvement when compared to the situation prior to regulation with a median Gini coefficient of 0.139. The distributions across the model runs of the Gini coefficient, in figure 6, show considerable overlap, suggesting that the environmental inequality issues with the efficient policies, in cases considered here, are of no greater concern than with the uniform standards. Using the Atkinson coeffi-

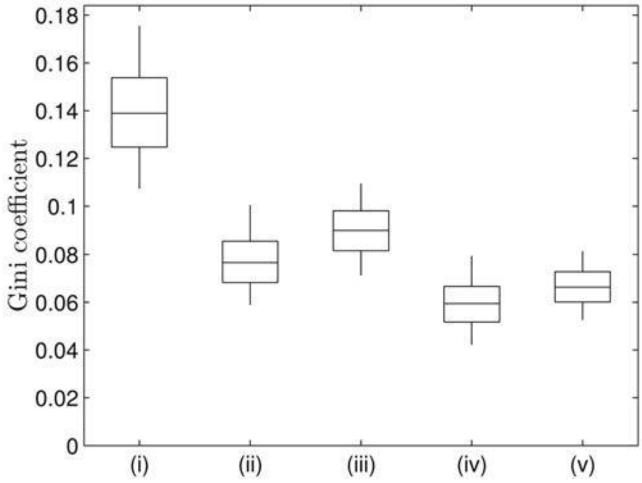

Figure 6. Distribution of Gini coefficient of inequality based on $PM_{2.5}$ concentration across 1,000 model runs: (i) initial situation without regulation, (ii) log-linear efficient abatement policy, (iii) log-linear "best" uniform standard, (iv) log-log efficient abatement policy, (v) log-log "best" uniform standard. Boxplot: center line represents median, top and bottom of box represent 25th and 75th percentiles, and ends of whiskers represent 5th and 95th percentiles.

cient, an alternative measure of inequality, the same pattern is found with inequality slightly lower under the efficient abatement policies than under the uniform standards.

2.2.2. Efficient Policy and Uniform Tax on Emissions

The above results indicate a strong social preference for an efficient abatement policy over a command-and-control style uniform pollution standard. Next we compare the importance of source-specific emission controls in the efficient policy to a cost-effective policy that does not differentiate the impact of emissions by source. Henry, Muller, and Mendelsohn (2011) find that SO_2 allowance trading in the United States actually increases damages relative to the no-trade baseline because it directs greater emissions to the dirtiest cities. The dirtiest cities tend to have the highest marginal costs of abatement as well as the highest marginal damages from emissions. By not differentiating between emissions at different sources, more emissions result in the areas with the highest marginal damages than is optimal.

Here we compare a uniform emissions tax to an efficient abatement policy that equates the marginal damages to the marginal costs of abatement for each source. The uniform emissions tax achieves a cost-effective outcome because sources choose a quantity of emissions to equate their marginal costs of abatement with the tax on emissions; however, because there is a single tax rate for the region, most or possibly all sources will be charged a tax that is not equal to the marginal damages from emissions. The uniform tax is a much simpler policy to administer than an efficient policy. We ask whether the distribution of marginal damages across sources is sufficiently spread out to favor an efficient policy over a uniform tax. Are the distributions of marginal damages sufficiently different between a log-linear and log-log C-R function to warrant different policies depending on the identified functional form?

The simulation results show that marginal damages vary greatly by source. Under the efficient abatement policy with both the log-linear and log-log C-R functional forms, marginal damages at the 95th percentile are nearly 3.5 times larger than at the 5th percentile. With a log-log C-R function the marginal damages are approximately 59% greater than with log-linear ($34,700 [log-linear], $55,100 [log-log], median marginal damages per ton). While the magnitude of the marginal benefits of abatement vary between the log-linear and log-log C-R functions, the distributions are quite similar. There is nearly perfect correlation between the marginal benefits of abatement by source with a log-linear and log-log C-R function. The form of the C-R function does not affect which sources are inflicting the greatest and least harm from pollution. Rather if the true C-R function is log-log all sources are contributing to greater damages than we previously believed.

How does the distribution of marginal benefits of abatement affect the outcomes from the efficient and uniform tax policies? Across the 1,000 model runs, the "best" uniform tax policy requires slightly greater emission reductions (23% for log-linear and 39% for log-log) than the efficient policy (22% for log-linear and 38% for log-log), yet the efficient policy has a greater impact on the population weighted average concentration (10.0 μg m^{-3} [log-linear], 8.6 μg m^{-3} [log-log]) compared to the uniform tax (10.3 μg m^{-3} [log-linear], 9.0 μg m^{-3} [log-log]; see fig. 7). The efficient policy generates 33% greater net benefits than the uniform tax with a log-linear C-R function, and 27% greater net benefits with log-log. The level of inequality in concentration between grid squares, as measured by the Gini coefficient, is very similar between the efficient policy and the uniform tax.

The advantage of the efficient policy is that it directs more abatement to the sources in the most populated grid squares, where the damages from emissions are greatest. With a log-linear C-R function, the efficient policy abates 32% of emissions from sources in grid squares in the top decile of population and only abates 9% of emissions from grid squares in the bottom decile. Under the uniform tax, with log-linear, all deciles abate 23% of emissions. With log-log, the efficient policy results in emission reductions of 51% from the top decile and 22% from the bottom decile. Under the uniform tax, with log-log, all deciles abate 39% of emissions. The uniform tax policy, which does not differentiate between emissions by source, leads to excessive emissions in the most populated areas.

Given the wide distribution of marginal benefits of abatement, and the resulting welfare advantage from efficient abatement, a policy that differentiates between the

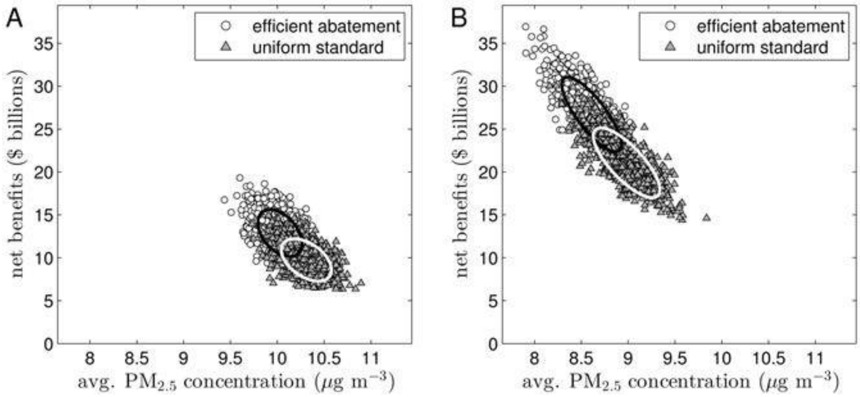

Figure 7. Efficient abatement policy versus uniform tax: net benefits of abatement and population-weighted average pollution concentration for each model run: log-linear C-R function (*A*), log-log C-R function (*B*). The four clusters each contain 1,000 points, of which 69%–71% are encircled by the respective ellipse. Each ellipse radius represents one standard deviation from the mean. The points inside each ellipse are the outcomes nearest the center of the joint distribution of $PM_{2.5}$ concentration and net benefits.

emissions by source appears warranted. In addition, the inefficient aspects of the uniform tax policy would be magnified if the tax were applied to a larger region with a wider distribution of marginal benefits.

Table 1 summarizes the median outcomes resulting from the three pollution control policies considered in the model. The efficient policy leads to the lowest concentration of fine particulates and greatest net benefits. The uniform concentration

Table 1. Comparison of Abatement Policies to Initial Situation without Regulation

	Δ Emissions (tons)	Δ Concentration (μg m^{-3})	Net Benefits ($billions)
Log-linear:			
Efficient policy	−700,000	−2.2	12.8
Uniform standard	−560,000	−1.5	5.8
Uniform tax	−740,000	−1.9	9.6
Log-log:			
Efficient policy	−1,230,000	−3.6	26.5
Uniform standard	−980,000	−2.5	13.4
Uniform tax	−1,260,000	−3.2	20.8

Note.—The change in concentration is the population weighted average across grid squares.

standard results in the worst outcomes utilizing a command-and-control abatement policy. A uniform tax on emissions outperforms the uniform standard by achieving a cost-effective outcome and results in the lowest total emissions of the three policies, but it provides insufficient incentives to the sources inflicting the greatest harm to limit emissions. Across the three policies, a log-log C-R function calls for lower emissions, lower concentrations of fine particulates, and greater net benefits of abatement compared to a log-linear functional form.

3. CONCLUSION

This paper contains a discussion of the effect of different shapes of a C-R function on environmental policy. An important distinction between the two functional forms considered is the impact on people facing the lowest concentration levels. If the log-log form reported in Krewski et al. (2009) is correct for fine particulates, then society may prefer substantially lower emissions. With the log-log functional form the benefits from a marginal unit of abatement are greater in clean locations than in dirty locations, all else equal. The log-log functional form leads to recommendations for significantly stricter pollution abatement policies, and correspondingly lower risks of mortality. Understanding the true shape of the C-R function between fine particulate concentrations and adult mortality is a worthy endeavor. Socially optimal policies are substantially different between the two functions.

The difference in policy outcomes between log-linear and log-log depends on the emissions within the area under the regulator's control. With greater unregulated emissions affecting concentrations within the area of interest, from emissions either outside the modeling domain or not subject to regulation within the region, the effectiveness of a policy achieving low concentrations is constrained, and the large potential risk reductions with log-log may not be attainable. Policies regulating all relevant emissions are crucial to realize the best possible outcomes.

Uniform pollution standards with command-and-control mechanisms to achieve the standards do not appear to be the economically preferred method of pollution control. We find that an efficient abatement policy leads to lower average concentrations while also achieving a better outcome for society. Environmental justice is a potential concern with an efficient abatement policy, because the focus is not on reducing risks for the most vulnerable populations. Contrary to our expectations, our results indicate that the level of inequality is similar or slightly less under an efficient abatement policy than under a uniform pollution standard, and both policies yield greater equality than conditions before abatement.

The application of Antweiler's (2012) idea for the iterative emissions tax to our computational problem appears to be interesting in its own right. He envisions an environmental regulator who actually adjusts the vector of source-specific taxes each period. That idea turns out to be powerful in an unexpected way: as the basis for a computationally efficient solution algorithm. The key to Antweiler's deep insight is that the regulator does not need to know abatement costs in order to guide the iterative policy to the optimum. Where his policy involves explicitly the passage of time, we use the same idea to solve an otherwise infeasible numerical problem that does not involve the passage of time. In both uses, Antweiler's and ours, regulated firms are assumed not to behave strategically in their response to each period's emission tax. If this assumption is not met, as in Moledina et al. (2003) and Kwerel (1977), and regulated sources anticipate the way their behavior in one periods feeds into the policy next period, one may expect the problem to become more difficult both computationally and in policy practice.

Our simulations identify the potential differences in outcomes and economically preferred policies between the two estimated Krewski et al. (2009) C-R functions. Application of this model to actual data, taken up in future work, will help to understand further the advantages and disadvantages of uniform environmental standards, such as the US National Ambient Air Quality Standards. This model also highlights the importance of source-specific policies, suggesting that greater scrutiny is needed on cost-effective policies that do not account for spatial differences in damages by source.

Our analysis focused on the policy implications of a supralinear C-R function at low concentrations. Supralinearity may be important for places that face much higher concentrations. At the highest concentrations globally, a supralinear C-R function indicates that risk reductions would be comparatively small until substantially lower concentrations are achieved (Evans et al. 2013).

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