# "The Choice Architecture of Choice Architecture: Toward a Nonpaternalistic Nudge Policy"

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**Characterizing Uncertainty in Air Pollution Damage Estimates.**

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Abstract

**Characterizing Uncertainty in Air Pollution Damage Estimates.**

This study uses Monte Carlo methods to characterize the uncertainty associated with per-ton damage estimates for 100 power plants in the contiguous United States (U.S.) This analysis focuses on damage estimates produced by an Integrated Assessment Model (IAM) for emissions of two local air pollutants: sulfur dioxide ($SO_2$) and fine particulate matter ($PM_{2.5}$). For each power plant, the Monte Carlo procedure yields an empirical distribution for the damage per ton of $SO_2$ and $PM_{2.5}$.For a power plant in New York, one ton of $SO_2$ produces \$5,160 in damages with a 90% percentile interval between \$1,000 and \$14,090. A ton of $PM_{2.5}$ emitted from the same facility causes \$17,790 worth of damages with a 90% percentile interval of \$3,780 and \$47,930. Results for the sample of 100 fossil-fuel fired power plants shows a strong spatial pattern in the marginal damage distributions. The degree of variability increases by plant location from east to west. This result highlights the importance of capturing uncertainty in air quality modeling in the empirical marginal damage distributions. Further, by isolating uncertainty at each module in the IAM we find that uncertainty associated with the dose-response parameter, which captures the influence of exposure to $PM_{2.5}$ on adult mortality rates, the mortality valuation parameter, and the air quality model exert the greatest influence on cumulative uncertainty. The paper also demonstrates how the marginal damage distributions may be used to guide regulators in the design of more efficient market-based air pollution policy in the U.S.

Keywords: Monte Carlo, Air Pollution, Market-based Pollution Policy,

# 1 Introduction

This study uses Monte Carlo methods to characterize the uncertainty associated with per-ton damage estimates for air pollution emissions from 100 power plants in the contiguous United States (U.S.). This analysis focuses on damage estimates produced by an Integrated Assessment Model (IAM) for emissions of two local air pollutants: sulfur dioxide ($SO_2$) and fine particulate matter ($PM_{2.5}$). The emphasis is on IAM-generated damage estimates because IAMs are commonly used to determine the effects of local air pollutants (Mendelsohn, 1980; Burtraw et al., 1998; Tong et al., 2006; Muller, Mendelsohn, 2007; 2009). Further, IAMs are often applied to evaluate public policies governing air pollution. As a result, characterizing model uncertainty has an important link to the development and evaluation of environmental policy (U.S. Environmental Protection Agency (USEPA), 1999). Such models are appealing in the context of air pollution because of their ability to connect emissions to concentrations and concentrations to their effects on society, typically through six elements: emissions, air quality modeling, concentrations, exposures, concentration-response relationships, and valuation. Parameters in each of these components of the IAM are derived from peer-reviewed literature in different scientific disciplines. The most common approach in applying IAM's is to employ the mean parameter values for the six elements listed above. However, this approach effectively ignores the influence of uncertainty in any one parameter and possible interactions across the input parameters. Since the process connecting emissions to damages is multiplicative (Rabl, Spadaro, 1999) cumulative uncertainty across the input parameters is especially important; this leads to log-normally distributed damage estimates which impacts inferential techniques. In this study we develop a stochastic IAM by drawing estimates of the uncertainty associated with emissions, air quality modeling, populations, dose-response, and valuation from the peer-reviewed literature. The stochastic IAM is then applied to model damages per ton for emissions of $SO_2$ and $PM_{2.5}$ at 100 power plants in the U.S. Although prior research has comprehensively modeled uncertainty in an IAM, this is the first study to apply a stochastic IAM to a large sample of power plants.

This paper uses the Air Pollution Emission Experiments and Policy analysis model (APEEP),

an IAM, which in prior applications, was used to produce deterministic estimates of the marginal damage of emissions for six pollutants[1] at nearly 10,000 sources in the contiguous U.S. (Muller, Mendelsohn, 2007; 2009). The simulation design in this study employs the algorithm to compute marginal damages described in Muller and Mendelsohn (2007). Briefly, this entails running the APEEP model using the U.S. Environmental Protection Agency's (USEPA) reported baseline emissions for the year 2002 and subsequently computing ambient concentrations, exposures, mortalities, and the value of premature mortalities (monetary damages) corresponding to the USEPA's emission data (USEPA, 2006). Next, one ton of one pollutant is added to a specific source and the APEEP model is run again computing exposures, mortalities, and damages. Since the only change between the two runs is the addition of one ton of pollution, the change in damages is the marginal ($/ton) damage of the chosen pollutant emitted from the chosen source.

In contrast to the prior applications of APEEP, this study employs Monte Carlo analysis to estimate the empirical distribution for the per-ton damage estimates for specific power plants. When modeling $SO_2$ damages the Monte Carlo algorithm involves the following steps. First, distributions with 10,000 observations are constructed for the input parameters. Next, one realization is randomly drawn from each of the input distributions and APEEP then computes baseline national damages. Following the computation of baseline damages, one ton of $SO_2$ is added to baseline emissions at a specific source, and the APEEP model is re-run using the same realizations drawn from each input distribution. Note that each iteration of the Monte Carlo simulation consists of both a baseline emission run and an "add-one-ton" run; each of these two runs uses the same set of randomly drawn values from the constructed distributions. This simulation design isolates the effect of the additional ton of $SO_2$ added to baseline emissions conditional on the random draws from the input distributions. This procedure is repeated 10,000 times for the selected source: once for each observation in the constructed distributions. The result of this procedure is a set of 10,000 estimates of the marginal damage of $SO_2$ emissions for the selected source. The algorithm is then repeated separately for other individual sources and for $PM_{2.5}$.

The paper focuses on damages per ton, or marginal damages. Estimating marginal damages,

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[1]The pollutants include: fine particulate matter ($PM_{2.5}$), coarse particulate matter ($PM_{10} - PM_{2.5}$), nitrogen oxides ($NO_x$), sulfur dioxide ($SO_2$), volatile organic compounds (VOC), and ammonia ($NH_3$).

rather than aggregate damages, is of particular importance for environmental policy since economic theory suggests efficient policy must equate marginal damages to marginal abatement costs – by source and by pollutant (see Baumol and Oates, 1988). The current regulatory climate for air pollution is increasingly moving towards market-based policy instruments; cap and trade schemes have gained widespread usage in the U.S., while both cap-and-trade as well as emission taxes are employed in the European Union (Goulder, Parry, 2008). The design of efficient market-based policies requires knowledge of the marginal damage of emissions. Specifically, the optimal tax rate for a specific source (similarly, the optimal permit price for cap-and-trade policies) is equal to the marginal damage of emissions caused by the source (Baumol, Oates, 1988). Because of the critical role that marginal damages potentially play in market-based policy design, information regarding the precision of the marginal damage estimates is clearly important for practitioners. Also, from an academic standpoint, characterizing and quantifying uncertainty and which parameters in the model contribute most to cumulative uncertainty will help to guide future research priorities, with the eventual goal of producing more precise marginal damage estimates.

As mentioned above, the Monte Carlo algorithm is applied to a sample of 100 power plants in the coterminous U.S. This produces empirical distributions for the damages per ton caused by emissions of both $SO_2$ and $PM_{2.5}$ emitted by each of the facilities. We embark on this process to explore how the revelations regarding the precision of the marginal damages might affect the design of pollution policy. Specifically, one way regulators could use the damage estimates is to just employ the mean damage by source. Then, if regulators pursue an efficient market-based policy, such as an emission tax, each facility with a distinct (mean) marginal damage would face a distinct tax rate - equal to its marginal damage. However, this tack disregards the degree of precision in the damage estimates. Another strategy regulators might use to design efficient market-based policy is to statistically test whether the marginal damages for the individual facilities are distinguishable from one another. This approach, which relies on having an empirical distribution for the marginal damages, has two advantages over just employing the means. First, by testing the equivalence of means for each pair of sources it builds the precision of the damage estimates into policy design. Second, the deterministic approach is problematic politically since applying a multiplicity of emission tax rates

to regulated firms is likely to be quite complicated and to generate considerable objections from firms. As a result, the second advantage of comparing the marginal damages statistically is that this will likely reduce the complexity of an efficient program by reducing number of emission tax rates. That is, any pair of sources whose mean damages are equivalent statistically are then subject to the same emission tax rate. This analysis takes the first step toward this approach to policy design by reporting the 90% percentile intervals for the marginal damages at 100 power plants in the U.S. The task of applying this method to the complete set of plants in the U.S. is left for future research.

With random draws from the constructed distributions at each stage of the model, the Monte Carlo algorithm provides an assessment of the cumulative impact of uncertainty in all stages of the APEEP model on source and pollutant specific marginal damage estimates. However, it is also of interest to determine the relative importance to total uncertainty of variability at each stage of the model. This is explored by setting one parameter equal to its mean value while all other parameters are modeled stochastically. The Monte Carlo procedure is then executed, producing 10,000 estimates of the source-specific, pollutant-specific marginal damage. With this estimated distribution, we compute the coefficient of variation and percentile intervals. We then compare the coefficient of variation (and the intervals) resulting from a particular parameter being held to its mean value with the coefficient of variation and the percentile intervals when all parameters are modeled stochastically. A large difference between the two coefficients of variation suggests that a certain parameter contributes a large share of cumulative model uncertainty. A small difference implies that the parameter has a limited influence on cumulative uncertainty. The thrust of these experiments is to help focus future research; by determining which parameters contribute most to cumulative uncertainty, these results may guide future research with the goal of providing more precise parameter estimates which will result in more precise marginal damage estimates.

This is not the first paper to explore statistical uncertainty in air pollution damage estimates. Specifically, Burtraw et al., (1998) report mean values and 90% confidence intervals associated with aggregate benefits of mandated emission reductions under Title IV of the Clean Air Act marginal damage estimates for nitrogen oxides and sulfur dioxide. However, these damage estimates

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were constructed using state-average damages not source-specific damages (Burtraw et al., 1998). Further, the confidence intervals reflect uncertainty in the valuation and dose-response parameters; they do not encompass emissions, populations, and air quality modeling.

Rabl and Spadaro, (1999) explore variability in marginal damage estimates for sulfur dioxide and nitrogen dioxide, and the uncertainty in several input parameters in an IAM. The contribution by the current analysis relative to the work of Rabl and Spadaro (1999) is two-fold. First, the current analysis characterizes uncertainty over a large sample of power plants throughout the coterminous U.S. whereas Rabl and Spadaro (1999) focus on general results not derived from a particular source or set of sources. The present paper therefore permits an assessment of how location and local land-use can affect the marginal damage distribution. Second, the work of Rabl and Spadaro (1999) is now over ten years old. Hence, the current study explores a more modern IAM and updated findings related to the input parameters in the IAM.

For the 100 power plants covered in this paper, we find that the empirical source-specific marginal damage estimates are quite variable with arithmetic coefficients of variation that range between 0.90 and 3.50. For a power plant in New York, one ton of $SO_2$ produces \$5,160 in damages with a 90% percentile interval between \$1,000 and \$14,090. A ton of $PM_{2.5}$ emitted from the same facility causes \$17,790 worth of damages with a 90% percentile interval of \$3,780 and \$47,930. At a power plant in Delaware, the $SO_2$ damage is estimated to be \$7,660 per ton, and the 90% interval reaches from \$1,550 to \$20,990. Further, the empirical marginal damages distributions appear to be well approximated by the lognormal distribution and the shape of the distributions are robust to whether the input parameters are distributed normally or lognormally. For both $SO_2$ and $PM_{2.5}$, the variability in the marginal damage estimates is driven by three input parameters: the transfer coefficients in the air quality models, the adult mortality dose-response coefficient, and the valuation parameter. The impact of the transfer coefficients is significantly greater for rural, western source locations than for urban, eastern sources. Variability in the infant mortality, emissions, and population parameters do not contribute appreciably to the cumulative uncertainty in the empirical marginal damage estimates. This analysis also shows that, for the full sample of 100 power plants, the marginal damage distributions follow a distinct spatial pattern; the degree

of variation observed in the distributions increases from east to west in the U.S. This implies that per-ton damage estimates for rural, western facilities are generally more uncertain than eastern, urban plants. This finding highlights the importance of capturing uncertainty due to air quality modeling.

Section 2. presents the theoretical model while section 3 describes the modifications to APEEP that capture uncertainty. A full description of the deterministic version of APEEP is available in Muller and Mendelsohn (2007). Section 4 presents our results and section 5 discusses the implications of the results both in terms of further research and pollution policy.

## 2    Theoretical Model

The empirical application of the IAM connects emissions from fossil fuel-fired power plants of pollutants to concentrations, exposures, physical effects, and dollar damages. The parsimonious theoretical model depicted in equations (1) through (5) describes the IAM in a series of five linear equations. This representation is adopted from Muller, Nordhaus, and Mendelsohn (2009). Equation (1) denotes emissions (E) of pollution species (s), emitted by a source in location (j), at time (t) as being a pollutant-specific function ($\Psi_s$) of fuel type (F), abatement technology (A), and volume of output $(Q)^2$.

$$E_{s,j,t} = \Psi_s(F_{j,t}, Q_{j,t}, A_{s,j,t}) \tag{1}$$

Equation (2) describes the ground-level concentration (C) of pollutant species (s), in receptor location (r) that is due to emissions from a source in location (j), at time (t). The relationship between emissions and concentrations is a function of the distance between source location and the concentration location as well as meteorological factors and chemical processes in the atmosphere. The different factors are captured in (2) by the function ($f_{s,j}$), which is dependent both on the pollution species (s) and source location (j).

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[2] The assumption in (1) is that emissions are a product only of fuel combustion and the level of output at a given emission source. This reflects the empirical context that focuses on fossil-fuel-fired power plants.

$$C_{s,r,j,t} = f_{s,j}(E_{s,j,t}) \tag{2}$$

The model computes exposures (X) to species (s) in receptor location (r), due to emissions by a source in location (j), at time (t), by multiplying the population of age-cohort (i) in location (r) at time (t), $(P_{r,i,t})$ times concentrations.

$$X_{s,r,j,t} = P_{r,i,t}C_{s,r,j,t} \tag{3}$$

The response (R) to exposures (X) are determined by the coefficient $(\beta_k^s)$, which is distinct for pollutant species (s), due to varying levels of toxicity, and for different health outcomes (k), such as premature mortality and acute illness.

$$R_{k,s,r,j,t} = \beta_k^s X_{s,r,j,t} \tag{4}$$

The monetary damage (V) due to the emissions of (s) from a source in location (j) in time (t) is shown equation (5). This is the sum, across receptor locations (r), and health outcomes (k), of the response (R) to exposures times the valuation coefficient $(\alpha_{k,t})$ , which translates physical effects into dollar values.

$$V_{s,j,t} = \sum_r \sum_k \alpha_{k,t} R_{k,s,j,t} \tag{5}$$

The marginal damage of an emission of pollutant species (s) from source (j) at time (t) is shown in (6).

$$MD_{s,j,t} = \left( \frac{\partial V_{s,j,t}}{\partial E_{s,j,t}} \right) \tag{6}$$

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In equations (1) through (6), each of the input parameters in the model are treated deterministically. This in turn leads to a single, deterministic value for the marginal damage of emissions shown in equation (6). In fact, the parent studies that report the values of the input parameters produce a mean and variance for these parameters[3]. When viewed from this perspective equations (1) through (5) are the product of a series of random variables. We denote these variables $(\hat{f}, \hat{\Psi}, \hat{P}, \hat{\beta}, \hat{\alpha})$.

Hence, $V_{s,j,t}$ and $\left(\frac{\partial V_{s,j,t}}{\partial E_{s,j,t}}\right)$ are no longer deterministic entities. Instead, $V_{s,j,t}$ and $\left(\frac{\partial V_{s,j,t}}{\partial E_{s,j,t}}\right)$ are now modeled as random variables resulting from the multiplicative process described in equations (1) through (5). Equation (7) expresses $(\hat{V}_{s,j,t})$ as a multiplicative function of the parameters shown above, with each parameter treated as a random variable.

$$\hat{V}_{s,j,t} = \sum_r \sum_k \hat{\alpha}_{k,t} \hat{\beta}_k^s \hat{P}_{r,t} (\hat{f}_{s,j}(\hat{\Psi}_s(F_t, Q_t, A_{s,t}))). \tag{7}$$

In this context, the APEEP model randomly selects a value from the distributions of the five random variables $(\hat{f}, \hat{\Psi}, \hat{P}, \hat{\beta}, \hat{\alpha})$. The APEEP model then computes $\hat{V}_{s,j,t,g}$ and $\left(\frac{\partial \hat{V}_{s,j,t,g}}{\partial \hat{E}_{s,j,t,g}}\right)$ where (g) denotes the $g^{th}$ draw from the empirical distributions for $(\hat{f}, \hat{\Psi}, \hat{P}, \hat{\beta}, \hat{\alpha})$.

$\hat{V}_{s,j,t}$ and $\left(\frac{\partial \hat{V}_{s,j,t}}{\partial \hat{E}_{s,j,t}}\right)$ are likely well-approximated by the lognormal distribution due to the multiplicative nature of the process described in equations (1) through (5). That is, the central limit theorem implies that the log-normal distribution is a good approximation for the distribution of a variable resulting from a multiplicative process (Slob, 1994; Rabl, Spadaro, 1999). As a result, confidence intervals based on normal distribution theory are problematic in this setting. The intervals reported in this paper are percentile intervals (Efron, Tibshirani, 1993). Specifically, the (1-$\alpha$) percentile intervals corresponding to the mean marginal damage of a for source (j), pollutant (s), at time (t) are computed using the formula shown in (8):

$$\left(\frac{\partial \hat{V}_{s,j,t}}{\partial \hat{E}_{s,j,t}}\right)^{\alpha}, \left(\frac{\partial \hat{V}_{s,j,t}}{\partial \hat{E}_{s,j,t}}\right)^{1-\alpha}. \tag{8}$$

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[3] For the function governing air quality modeling $(f_n)$, estimates of associated variability are not readily available in the literature. As a result, a regression analysis-based estimate of such variability is produced in this paper. This procedure is discussed in section 3.

For a 90% interval, $\alpha = 0.05$, and $\left(\frac{\partial \hat{V}_{s,j,t}}{\partial \hat{E}_{s,j,t}}\right)^{\alpha}$ corresponds to the $(N \ x \ \alpha)$ observation from the ordered distribution for $\left(\frac{\partial \hat{V}_{s,j,t}}{\partial \hat{E}_{s,j,t}}\right)$. Similarly, $\left(\frac{\partial \hat{V}_{s,j,t}}{\partial \hat{E}_{s,j,t}}\right)^{1-\alpha}$ corresponds to the $(N \ x \ (1-\alpha))$ observation from the ordered distribution. The ordered distribution ranks the (G) observations of $\left(\frac{\partial \hat{V}_{s,j,t}}{\partial \hat{E}_{s,j,t}}\right)$ in ascending fashion. With G = 10,000, $\left(\frac{\partial \hat{V}_{s,j,t}}{\partial \hat{E}_{s,j,t}}\right)^{\alpha}$ reflects the $500^{th}$ observation while $\left(\frac{\partial \hat{V}_{s,j,t}}{\partial \hat{E}_{s,j,t}}\right)^{1-\alpha}$ corresponds to the 9,500$^{th}$ observation in the ranked vector of $\left(\frac{\partial \hat{V}_{s,j,t}}{\partial \hat{E}_{s,j,t}}\right)$.

The following section describes how the APEEP model is used to estimate $\left(\frac{\partial \hat{V}_{s,j,t}}{\partial \hat{E}_{s,j,t}}\right)$.

# 3 Empirical Model.

The empirical component of this study relies on the Air Pollution Emission Experiments and Policy Analysis model (APEEP): (Muller, Mendelsohn 2007). The structure of APEEP is shown in figure 1. For a complete, detailed description of APEEP see Muller and Mendelsohn (2007). The modifications to the version of the model in prior applications (Muller and Mendelsohn, 2007; 2009; Muller, Nordhaus, Mendelsohn, 2009) consists of explicitly modeling the uncertainty associated with each stage of the model. Hence, the new stochastic version of APEEP creates distributions around the input parameters, with the measures of dispersion taken from the peer-reviewed studies that report the input parameters that are used in APEEP (Pope et al., 2002; USEPA, 1999; Kuykendal, et al., 2006; Stoto, 1983; Woodruff et al., 2006). An additional modification to prior versions of APEEP involves the marginal damage algorithm which is described in the following section.

## 3.1 The Marginal Damage Algorithm with Uncertainty

To model the impact of uncertainty at each stage of APEEP and its combined influence on the marginal damage estimates, we use the algorithm for computing marginal damages developed in Muller, Mendelsohn (2007). This entails running the APEEP model using the USEPA's reported baseline emissions for the year 2002 and computing exposures, mortalities, and monetary damages corresponding to the USEPA's emission data (USEPA, 2006). Next, one ton of one pollutant is added to a specific source and the APEEP model is re-run computing exposures, mortalities, and damages. Since the only change between the two runs is the addition of one ton of pollution, the

change in damages is the marginal damage, expressed in terms of dollars per ton, of the chosen pollutant emitted from the chosen source.

The Monte Carlo analysis features the construction of distributions for the emissions, air quality modeling, exposure, dose-response, and valuation modules. These are based on the values reported in table 1 in the appendix. Each iteration of the Monte Carlo procedure consists of the following six steps.

1) Take $g^{th}$ random draw from input distributions.

2) APEEP computes $g^{th}$ realization for emissions, concentrations, exposures, physical effects, and damages.

3) APEEP adds one ton of pollutant species (s), to source (j).

4) APEEP recomputes (using for $g^{th}$ realization) concentrations, exposures, physical effects, and damages given +1 ton of pollutant species (s) at (j).

5) APEEP computes the difference between damages in step (4) and in step (2).

6) Repeat steps (1) through (5) 9,999 times.

Following from above, the first step in the Monte Carlo algorithm is a random draw from each of the input distributions. Next, the model computes concentrations, exposures, physical effects, and damages given the random draw on emissions. Then one ton of a specific pollutant (s) is added to the emissions for a specific source (j). APEEP then recomputes concentrations, exposures, physical effects, and damages given the random draw on emissions plus the additional ton. Since the damages after the addition of one ton are computed with the same draws from the distributions, the difference in damages between steps (2) and (4) is strictly attributable to adding the experimental ton to the selected source. And the difference in damages - computed in step (5) - between the two runs is the marginal damage of emissions for the specific pollutant added to the particular source conditional on the $g^{th}$ draw from the input parameter distributions. As shown in step (6) this procedure is repeated 10,000 times for a single source and pollutant. The end result is that for the chosen source, 10,000 different values are obtained for the marginal damages, which effectively provides an empirical distribution for the marginal damage. These distributions are used

to derive 95% confidence intervals for the mean marginal damages for the 100 power plants covered in this paper. The following sections briefly describe the methods used to construct distributions for emissions, air quality models, populations, dose-response and valuation. For the measures of dispersion used to construct the input distributions, see the appendix.

The adaptation of APEEP from its deterministic version that was used in prior research (Muller, Mendelsohn, 2007;2009) to the stochastic version begins by constructing a distribution around the mean emission estimates provided in USEPA's emission inventory for the year 2002 (USEPA, 2006). This study focuses on modeling emissions from fossil fuel-fired power plants. Emissions from these sources are measured using the USEPA's Continuous Emission Monitoring System (CEMS). Although discharges from such sources are measured, the potential for uncertainty due to measurement error exists (Frey, Zheng, 2002; Frey, Li, 2003; Abdel-Aziz, Frey, 2004; Kuykendal, et al., 2006). The estimated ranges of variability in Kuykendal, et al., (2006) are used herein (see table 5).

The air quality model in APEEP relies on a source-receptor matrix framework (Muller, Mendelsohn, 2007). Each transfer coefficient in the matrix is denoted ($T_{j,s,r}$); these represent the change in annual average concentration of pollutant species (s), in receptor location (r), due to emissions in source location (j) (Latimer, 1996; Muller and Mendelsohn, 2007). The air quality modeling literature that focuses on Gaussian models (Turner, 1994) suggests that the variability in transfer coefficients is typically an increasing function of the distance between (j) and (r). As a result, we estimate the variation in $T_{j,s,r}$ in a manner that reflects the relationship between distance and variation in the ($T_{s,j,r}$). Specifically, the transfer coefficients are split into four different categories of distances (d) between (j) and (r): 0 to 100 miles, 100 to 500 miles, 500 to 1000 miles, and 1000 to 3,000 miles. To model the variability in the ($T_{j,s,r,d}$)[4] a regression model is estimated which describes the ($T_{j,s,r,d}$) as a linear function of the distance between the source (j) and receptors (r) as shown in (8),

$$T_{s,j,r,d} = \theta_{0s,d} + \theta_{1s,d}D_{j,r} + \varepsilon_{s,j,r,d} \tag{9}$$

[4]Note the addition of the subscript (d) which denotes distance category.

where $D_{j,r}$ is the distance from the source (j) to the receptor (r), the $\{\theta\}$ are OLS parameter estimates for pollutant species (s) and distance category (d), and $\varepsilon_{s,j,r,d}$ is a stochastic term.

Within each distance category, the model in (8) is estimated using the set of $T_{j,s,r,d}$ from the source-receptor matrix (there are distinct matrices for $SO_2$ and for $PM_{2.5}$) and the corresponding distances for each (j,r) pair. For each of the distance categories, a unique standard error estimate for the transfer coefficients is obtained, using a bootstrap procedure as follows (Efron, Tibshirani, 1993). This involves drawing samples of the $T_{j,s,r,d}$ (with replacement) from one of the four distance categories specified above. For each of these samples, the model in (8) is estimated, from which a set of predicted values, denoted $(\hat{T}_{j,s,r,d})$ are obtained. For each bootstrap sample, APEEP computes the mean and the standard deviation of the predicted surface (the $\hat{T}_{j,s,r,d}$). After drawing 10,000 bootstrap samples, we obtain a sample of 10,000 mean values for from which the standard error is estimated. Using this technique for each of the distance categories (separately), we obtain four values for the uncertainty in the transfer-coefficients, one for each distance category. This procedure is executed separately for $SO_2$ and $PM_{2.5}$.

Exposures are computed as population times concentrations. Concentrations vary with each iteration of the Monte Carlo procedure due to the different draws from the distributions around the mean emission estimates and the transfer coefficients. Uncertainty in human populations is modeled using estimates of the error in the U.S. Census Bureau's population projections (Stoto, 1983).

The dose-response module translates exposures to pollution into physical effects. In this study, we concentrate on the uncertainty associated with estimates of the impact that exposures to $PM_{2.5}$ have on mortality risk for both adults and infants. Such uncertainty is associated with, $\beta_{i,k}^s$, the parameter that relates changes in ambient pollution into changes in age-specific mortality rates shown in equation (4). We derive distributions for $\beta_{i,k}^s$ using the standard errors reported in Woodruff, Parker, and Schoendorf (2006), for infant mortalities, and Pope, et al., (2002) for adult mortalities.

In the valuation module, APEEP affixes a dollar value to the physical effects estimated in the dose-response module. This study focuses on mortality effects, hence we focus here on modeling

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uncertainty associated with the valuation of small changes to mortality risks. The uncertainty associated with the valuation parameter, $(\alpha_{k,t})$ in equation (5), for premature mortality is derived from a meta-analysis of roughly 30 studies (USEPA, 1999). This parameter has a mean of roughly $6 million (year-2000 U.S. dollars).

In addition to modeling cumulative uncertainty, APEEP is used to explore the influence of uncertainty on each input parameter on cumulative uncertainty. The procedure models each input parameter in the model stochastically except one; this parameter is set to its mean value. Then, with this particular parameter fixed at its mean value the Monte Carlo procedure is executed 10,000 times to generate an empirical distribution of the marginal damages. For a specific source and pollutant, this is repeated for each parameter in APEEP. Using this estimated distribution, we estimate the arithmetic coefficient of variation, $CV_{j,s,m} = (\frac{\sigma}{\mu})$, for source (j) and pollutant (s), and the $(m^{th})$ parameter.

# 4    Results

Table 1 reports the mean and the 90% percentile intervals for the empirical distribution of the marginal damage estimates for both sulfur dioxide $(SO_2)$ and fine particulate matter $(PM_{2.5})$ corresponding to four fossil fuel-fired power plants; the facilities are located in Indiana (IN), New York (NY), Texas (TX) and Delaware (DE). The sites were chosen from the sample of 100 power plants as test cases. The input distributions are log-normal[5]. The results in table 1 indicate that one ton of $SO_2$ emitted from the power plant in New York produces $5,160 in mortality damages. The $5^{th}$ percentile is $1,000 while the $95^{th}$ percentile is $14,090. A ton of $PM_{2.5}$ emitted from the same facility causes $17,790 worth of damages with $5^{th}$, and $95^{th}$ percentiles of $3,780 and $47,930. A similar interpretation holds for the other facilities listed in table 1. Note that all power plants have empirical marginal damages that are characterized by a long right tail; the difference between the mean and the $95^{th}$ percentile is greater than the difference between the mean and the $5^{th}$ percentile.

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[5] Table 3 and figures 1 - 2 in the appendix  show that the damage distributions are robust to whether the input parameters are normally or lognormally distributed.

This is the first evidence that the marginal damages are distributed log-normally.

Focusing on the mean values for $PM_{2.5}$ reported in table 1, the greatest damages per ton are associated with emissions from the facility in New York with damages becoming smaller for emissions from Delaware, Indiana, and Texas. Since the damages modeled by APEEP focus on mortalities this is an intuitive result given the relative population densities proximal to each plant. Looking at the mean damages for $SO_2$, the pattern is slightly different than that for $PM_{2.5}$. The facility in Delaware generates the greatest damage per ton, with damages then descending for New York, Indiana, and Texas. This result occurs because when $SO_2$ is emitted it takes some time (and therefore distance if the wind is blowing) before it turns into $PM_{2.5}$. With prevailing westerly winds, the emissions in Delaware blow into the New York metropolitan area after the $SO_2$ has been converted into $PM_{2.5}$. In contrast, the $SO_2$ emissions in New York are transported by prevailing winds out of the metropolitan area before they turn into $PM_{2.5}$. An additional pattern in table 1 is that the damages due to emissions of $PM_{2.5}$ are uniformly more harmful than emissions of $SO_2$. This occurs because only a fraction of emitted $SO_2$ transforms into constituents of $PM_{2.5}$ and, therefore, affects mortality rates.

Table 1 also reports the mean marginal damages when all input parameters are modeled deterministically. Each of the deterministic marginal damages for $SO_2$ are smaller in magnitude than the stochastic mean marginal damages. The difference between the stochastic marginal damages and the mean marginal damage ranges between 0.5% for the Texas power plant and 3% for the facilities in Delaware and Indiana. For $PM_{2.5}$, the deterministic marginal damages are also smaller than the stochastic means for each of the facilities except for the plant in Texas. The facilities in Indiana, Delaware, and New York have deterministic marginal damages that are between 1% and 3% smaller than the corresponding stochastic means. The deterministic marginal damage is 10% greater than the stochastic mean marginal damage at the Texas facility.

Figure 2 displays box plots corresponding to the $SO_2$ marginal damage estimates for four fossil fuel-fired power plants drawn from the full sample of 100 plants covered in this study. These are the facilities shown in table 1. The box plots reveal that the empirical marginal damage estimates appear to be highly right-skewed. The median line is below the center of each box. Further, the

distributions each contain a long right tail[6]. As reported in prior research (Rabl, Spadaro, 1999) the multiplicative nature of the process drives the right-skewed quality of the damage distributions. The right-skewed nature of the distributions is robust to whether we assume that the input distributions are either lognormally or normally distributed. This is the second piece of evidence suggesting that the distributions are log-normal.

Additionally, the facility in Delaware has the largest median marginal damage, and the greatest interquartile range. The facility in Texas has both the smallest median damage and the smallest interquartile range. Figure 3 displays the box plots corresponding to $PM_{2.5}$ damages for the same four power plants. The similarity between figure 2 and figure 3 is striking; all power plants exhibit right-skewed distributions in their damage distributions, and the ranking of both the medians and the degree of dispersion in the damage distributions is nearly the same as was observed in figure 2. The difference is that, for $PM_{2.5}$, the New York facility has the largest median damage and the largest spread.

The left-hand side of table 2 reports the mean $SO_2$ damage per ton, 90% percentile intervals, and the arithmetic coefficient of variation (as defined in section 2) for 10 of the facilities from the full sample of 100 power plants. These 10 plants were selected because they have the largest coefficients of variation for $SO_2$ damages. All of the facilities in table 2 are located west of the Mississippi River. Figure 4 maps the coefficient of variation associated with the distribution of $SO_2$ damages per ton for all of the 100 power plants across the U.S. This figure reveals the pattern that table 2 suggests; the coefficient of variation is larger for power plants located in the western U.S. This occurs because, in the west, emitted $SO_2$ has to travel long distances before it encounters population centers. Hence, the long-range dispersion aspect of the air quality model in the IAM is dictating most of the exposures from such emissions. And, as stated above the variability of the transfer coefficients in the air quality models is generally an increasing function of distance between the emission source and receptor locations (see table 2 in the appendix). In contrast, emissions from power plants located east of the Mississippi River do not have to travel great distances before they affect large urban areas. As a result, for such facilities the transfer coefficients in the stochastic

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[6]Note that the values beyond the whiskers are not shown in figure 1.

air quality model that govern the majority of eventual exposure are much less variable and the empirical distributions for the associated marginal damages are also less variable (as revealed by their smaller coefficients of variation)[7].

The right-hand side of table 2 displays the mean $PM_{2.5}$ marginal damage, the corresponding 90% percentile intervals, and the coefficient of variation for the 10 plants with the largest coefficient of variation for $PM_{2.5}$. Much like the results for $SO_2$ the spatial pattern is striking in that, of the 100 power plants in the sample, the 10 with the greatest degree of variability in the $PM_{2.5}$ damages are all located in the western half of the U.S. As with $SO_2$, this pattern occurs because, for power plants located in the west, emissions must be transported great distances before they impact population centers. The relationship between emissions from rural sites and exposure are governed by the long-range dispersion parameters in the air quality model which are more variable than short range coefficients (which govern emissions from facilities close to cities). Figure 5 maps the coefficient of variation associated with the distribution of $PM_{2.5}$ marginal damages for the 100 power plants across the U.S. Like figure 4, this map shows the gradient in the coefficient of variation from east to west.

An interesting application of the findings reported in table 2 is to use the percentile intervals to draw inferences regarding distinctions between the mean damages per ton. That is, by testing whether the 90% percentile intervals for each pair of sources overlap, we can determine if the marginal damages are statistically different from one another. Recall that economics suggests that an efficient regulatory program (such as an emission tax) sets emission tax rates equal to the marginal damage of emissions, on a source-specific basis. For $\alpha = 0.10$, any two sources in table 2 that have overlapping percentile intervals would be subject to the same emission tax rate. For the twenty power plants listed in table 2, if a regulator employed the mean marginal damage to calibrate emission taxes, they would set twenty distinct tax rates: one rate corresponding to the marginal damage caused by each facility's emissions of each pollutant. This is a deterministic approach to the design of an emission tax policy.

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[7]The one notable exception to the observed east-west gradient is a power plant located in Maine (the farthest to the northeast on figure 4). Although the estimated coefficient of variation for this facility is larger than other eastern plants, the logic behind the results in figure 4 still hold because, this facility is located some distance from the major eastern cities (especially given prevailing westerly winds).

However, the percentile intervals reported in table 2 indicate that such a design is overly nuanced because the 90% confidence intervals for all of these sources overlap. Beginning with $SO_2$, the first two sources (located in Texas and Missouri) have statistically equivalent marginal damages at $\alpha = 0.10$. Therefore, these two sources would have their emissions of $SO_2$ taxed at an equivalent rate[8]. Proceeding down through the left-hand side of table 2, it is clear that all the sources have overlapping confidence intervals at $\alpha = 0.10$.

The same analysis applied to the right-hand side of table 2, which focuses on $PM_{2.5}$, suggests that one tax rate would efficiently govern the 10 power plants listed therein. This implies that if the regulator intends to design an efficient emission tax regime for the power plants listed in table 2, this approach to the design of market-based air pollution policy reduces the complexity of the emergent policy - the number of tax rates decreases significantly. As such, this approach builds the precision of the damages estimates directly into the regulatory program. This application of the results in table 2 has powerful implications for the design of air pollution policy since it is likely to dramatically simplify an efficient program.

This application of table 2 does not imply that all power plants in the U.S. have statistically equivalent marginal damages. The power plants shown in table 2 are those with the most variable marginal damage distributions; so one would expect a high degree of overlap among them. Looking back at the full sample of 100 facilities, one can test for equivalent damages among plants located in different regions, where one might suspect significant differences in damages per ton of emissions. For instance, by comparing plants in large urban areas in the eastern U.S. with the rural western facilities. Indeed, for $PM_{2.5}$ four facilities located in, and upwind from, New York City generate marginal damages that are distinct (at $\alpha = 0.10$) from the damages caused by $SO_2$ emissions from a facility in rural Texas.

Table 3 explores the influence that uncertainty in each input parameter has on the total variation in the empirical marginal damage distributions. Table 3 reports the coefficient of variation corresponding to six scenarios for each pollutant and each of the four facilities modeled in table 1. Each scenario features one of the input parameters set to its deterministic value with all other

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[8]The efficient tax rate would be the mean marginal damage of either source since they are equivalent at $\alpha = 0.05$.

parameters modeled stochastically. Note the top row of the table reports the coefficient of variation when all parameters are stochastic. Table 3 is interpreted as follows; values of the coefficient of variation that differ substantially from the "all uncertain" run indicate that the deterministic parameter has a strong influence on total uncertainty. Alternatively stated, when the uncertainty associated with an input parameter is removed by setting the parameter to its deterministic value, if the variation in the joint distribution is considerably less than the original joint distribution (with all input parameters modeled stochastically) then one may conclude that the deterministic parameter has a strong impact on the uncertainty in the joint distribution.

For $SO_2$, results from all four facilities indicate that mortality valuation, the adult mortality dose-response coefficient, and air quality modeling have the strongest effect on cumulative uncertainty. Conversely, emissions, population, and infant dose-response have a limited effect. Also, the coefficient of variation is greater for the facilities in Indiana and Texas than for the plants in New York and Delaware. This supports table 2 and figure 4 in that the degree of variability in the empirical distributions increases from east to west. For $PM_{2.5}$ the results are similar to those for $SO_2$ in that, air quality modeling, mortality valuation, and the adult mortality dose-response coefficient contribute the most to cumulative uncertainty in the marginal damage estimates. Further, the coefficient of variation for the four power plants covered in table 3 for $PM_{2.5}$ displays the same pattern as for $SO_2$ and this pattern supports the results in table 2. Namely, the coefficient of variation increases for facilities located in the western U.S. Specifically, the coefficient of variation for the facility in Texas is 3.10 with all parameters modeled stochastically, 1.79 for the plant in Indiana, 0.95 for the facility in Delaware, and 0.91 for the power plant in New York. Like $SO_2$, source location has a strong impact on the variation in per ton damage estimates for $PM_{2.5}$.

Table 4 reports the 90% intervals corresponding to the simulations in which one input parameter in modeled deterministically. These results translate the changes in the coefficient of variation in table 3 into changes in the span of the percentile intervals. Several results are worth noting. First, for $SO_2$ emissions from the rural facilities in Indiana and Texas, the impact of uncertainty in air quality modeling is evident. The $95^{th}$ percentile for the Indiana facility decreases from \$12,660 to \$8,860 when the deterministic air quality model is employed. This is a reduction of 30%. The $5^{th}$

percentile increases by 2.6 times. For the Texas plant, the $95^{th}$ percentile decreases by 23% from $8,250 to $6,370. The $5^{th}$ percentile increase by a factor of three. Table 4 shows that the change in the percentile intervals for the facilities in Delaware and New York are significantly smaller.

Table 4 also indicates that treating the mortality valuation parameter deterministically has a dramatic impact on the width of the percentile intervals. While the narrowing of the intervals occurs for all facilities, the impact of the mortality valuation parameter is most acute for the Delaware and New York plants. The $95^{th}$ percentile declines by 26% for $SO_2$ and 23% emitted at Delaware, respectively. Similarly, the $95^{th}$ percentile decreases by 23% for $SO_2$ and 26% emitted at New York, respectively.

Table 5 explores the impact that emission height has on the marginal damage distributions. Ground level emissions are produced by both mobile sources (cars, trucks, marine vessels, and trains) and stationary sources (households, and commercial facilities without a tall smokestack). This set of experiments explores the influence of emission height on the statistical distribution of marginal damages by comparing the distributions for power plants with the distribution for ground sources in the same physical location, we are able to isolate the impact of emission height on the emergent distributions.

The left side of table 5 displays the coefficients of variation for the distribution of marginal damages corresponding to emissions from a ground-level source in New York. The right-hand side of table 5 includes data from table 3 corresponding to the power plant in New York. The first important result shown in table 5 is that the coefficients of variation for the ground source distribution are considerably larger than for the power plant distribution; this implies that the marginal damage estimates are significantly more variable for the ground-level source than for the power plant. An additional interesting result shown in table 5 are the similarities in magnitudes of the coefficients of variation across the input parameters. That is, for $SO_2$ emissions from the power plant, mortality valuation, adult mortality dose-response, and air quality modeling have the greatest impact on cumulative uncertainty. For the ground source, air quality modeling, dose-response, and mortality valuation have an appreciable impact on cumulative uncertainty. For $PM_{2.5}$ emissions from the power plant, mortality valuation and adult mortality dose-response have

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the largest effect on cumulative uncertainty. For $PM_{2.5}$ emitted from the ground source, air quality modeling, adult mortality dose-response, and mortality valuation have an appreciable impact on cumulative uncertainty.

Table 6 reports the 90% percentile intervals for both the ground source and the power plant in New York. The magnitudes both of the mean marginal damage and of the width of the percentile intervals for the ground source are significantly larger than the power plant. With all parameters uncertain, the interval for $PM_{2.5}$ ranges from \$36,000 to \$611,000. For $SO_2$, the interval stretches from \$6,900 to \$129,000. The width of the percentile intervals explains the considerably larger coefficients of variation reported in table 5. Further, uncertainty in both the mortality dose-response parameter and the mortality valuation parameter have significant impacts on the empirical distribution for the ground source marginal damages. Modeling the valuation parameter deterministically reduces the $95^{th}$ percentile by approximately 20% for $PM_{2.5}$, and $SO_2$. Treating the dose-response parameter as uncertain decreases the upper bound the percentile intervals by roughly 15% for both pollutants.

Figures 6, 7, and 8 map the health damages due to an emission of $SO_2$ from the fossil fuel-fired power plant in Indiana. Figure 5 displays the health damages, by county of occurrence, when the marginal damage estimate corresponds to the mean of the distribution of possible marginal damage values; table 1 indicates that the median value is approximately \$2,780 for emissions of $SO_2$ from this facility. Figure 5 indicates that the counties with relatively large damages due to emissions from this plant encompass large midwestern cities: Chicago, Indianapolis, Detroit, and Cincinnati are labeled on the map. In addition, emissions from this facility also impact counties along the east coast cities. However, figure 3 indicates that these effects are quite small; most counties along the east coast incur health damages that are less than \$10/ton. Figure 6 displays the spatial distribution of damages when the marginal damage is in the $1^{st}$ percentile of the distribution. The difference in the spatial distribution of damages between the $1^{st}$ percentile case and the mean case is dramatic; only the midwestern cities show up on the map, with no other counties incurring detectable damages due to emissions from the facility in Indiana. In this extreme case, emissions have no discernible impact on the east coast cities. At the other end of the distribution is the $99^{th}$ percentile case

shown in figure 7. In this case, emissions have a strong impact over a broad range of counties from the midwest to the east coast cities. These final experiments show the differences in magnitude and in the spatial pattern in damages due to emissions of an additional ton of $SO_2$ for different realizations from the input parameter distributions.

# 5    Conclusions

This study explores the nature of statistical uncertainty associated with per-ton damage estimates for $SO_2$ and $PM_{2.5}$ generated by an integrated assessment model (APEEP), (Muller, Mendelsohn, 2007;2009). The analysis finds that the marginal damage estimates are log-normally distributed due to the multiplicative process that produces the marginal damage estimates in the APEEP model. Further, for a sample of 100 power plants the $PM_{2.5}$ and $SO_2$ marginal damages are highly variable; the coefficients of variation for the estimated distributions range between 0.90 and 3.50. This analysis also shows that, for both $PM_{2.5}$ and $SO_2$, the marginal damage distributions follow a distinct spatial pattern; the degree of variation observed in the distributions increases from east to west in the U.S. This occurs because, for western power plants, emissions have to travel longer distances before they encounter cities. The variability of the transfer coefficients in the air quality models is typically an increasing function of distance between the emission source and receptor locations. In contrast, emissions from eastern power plants affect large urban areas that are nearby. For such plants the transfer coefficients in the stochastic air quality model that govern exposure are much less variable; so are the resulting empirical distributions for the associated marginal damages. This implies that for $PM_{2.5}$ and $SO_2$ per-ton damage estimates for rural, western facilities are generally more uncertain than eastern, urban plants. This finding highlights the importance of capturing uncertainty due to air quality modeling.

The degree of variation found in this study may have important implications for the design of regulations intended to govern these pollutants. Specifically, damage estimates are used by regulators in two primary ways. First, regulators such as the USEPA are required to conduct cost-benefit analyses of major regulations such as the Clean Air Act. To do so USEPA employs

IAMs that are similar in form to APEEP. The results from this study are likely to assist regulators in calculating and reporting confidence intervals on the avoided damages due to environmental regulations. While USEPA and others have reported such confidence intervals in the past, they have either not included uncertainty at each stage of the integrated assessment model or the models used were antiquated relative to APEEP. Second, regulators intending to design and implement market-based policies such as cap-and-trade and emission taxes can use marginal damage estimates produced by IAMs to calibrate tax rates and aggregate caps. The results in this study may help regulators to gain a better sense of the degree of precision of these estimates which is critical in such an application of IAM-generated damage estimates.

An important contribution of this study is the decomposition of cumulative uncertainty into its component parts. This is achieved by executing a Monte Carlo analysis with all input parameters modeled stochastically and comparing the marginal damage distributions to those computed when individual input parameters are treated deterministically. This approach isolates the influence of specific input parameters on cumulative uncertainty. Pursuing this strategy, we find that for air quality model parameters, mortality valuation, and adult mortality dose-response parameters have the greatest impact on cumulative uncertainty. However, we also determine that the impact of uncertainty in the air quality modeling parameters is much more pronounced for sources in rural areas than for sources in urban areas.

Table 1:

Empirical Distributions of Marginal Damages.

| Facility | Stochastic | | Deterministic | |
|---|---|---|---|---|
| | SO$_2$ | PM$_{2.5}$ | SO$_2$ | PM$_{2.5}$ |
| NY | 5,160 (1,000, 14,090) | 17,790 (3,780, 47,930) | 5,060 | 17,360 |
| TX | 2,400 (180, 8,250) | 2,400 (180, 8,250) | 2,390 | 2,650 |
| IN | 4,300 (650, 12660) | 4,810 (620, 15,080) | 4,180 | 4,770 |
| DE | 7,660 (1,550, 20,990) | 10,250 (2,030, 28,160) | 7,460 | 10,040 |

Mean values expressed in $/ton/year.

5%, 95% Percentiles in parenthesis (Lower:Upper)

Table 2:
Uncertainty in $SO_2$ and $PM_{2.5}$ Marginal Damage Estimates:
Ten Most Variable Distributions.

| Pollutant | $SO_2$ | | | $PM_{2.5}$ | | |
|---|---|---|---|---|---|---|
| Facility Location | Mean (5%,95%) | CV | Facility Location | Mean (5%,95%) | CV |
| Texas | 1,360 (80:4,720) | 2.86 | Arizona | 2,200 (120:7,370) | 3.47 |
| Nevada | 1,330 (110:4,350) | 2.85 | Texas | 2,070 (140:6,780) | 3.23 |
| Utah | 1,370 (140:4,300) | 2.60 | North Dakota | 2,540 (140:8,530) | 3.18 |
| Missouri | 1,300 (90:4,400) | 2.49 | Colorado | 2,350 (210:7,170) | 3.15 |
| Arizona | 2,190 (160:7,570) | 2.48 | North Dakota | 2,580 (150:8,650) | 3.13 |
| Iowa | 1,500 (110:5,110) | 2.34 | New Mexico | 2,190 (180:6,900) | 3.11 |
| Kansas | 1,350 (110:4,500) | 2.33 | Texas | 2,680 (200:8,640) | 3.10 |
| Texas | 2,400 (180:8,250) | 2.29 | Colorado | 2,450 (230:7,500) | 3.04 |
| Colorado | 2,180 (200:7,190) | 2.28 | Utah | 1,660 (220:4,600) | 3.00 |
| Nebraska | 1,530 (120:5,170) | 2.27 | Nevada | 1,640 (160:5,210) | 2.97 |

Mean values expressed in \$/ton/year.

5%, 95% Percentiles in parenthesis

CV =Arithmetic Coefficient of Variation $\left(\frac{\sigma}{\mu}\right)$.

The Influence of Input Parameters on Cumulative Uncertainty

| Facility | IN | | DE | | NY | | TX | |
|---|---|---|---|---|---|---|---|---|
| Deterministic Parameter | SO$_2$ | PM$_{2.5}$ | SO$_2$ | PM$_{2.5}$ | SO$_2$ | PM$_{2.5}$ | SO$_2$ | PM$_{2.5}$ |
| All Uncertain | 1.31 | 1.79 | 0.93 | 0.95 | 1.00 | 0.91 | 2.29 | 3.10 |
| Emissions | 1.31 | 1.77 | 0.93 | 0.95 | 1.00 | 0.91 | 2.29 | 3.10 |
| Air Quality Model | 0.86 | 0.86 | 0.87 | 0.87 | 0.86 | 0.87 | 0.85 | 0.85 |
| Population | 1.31 | 1.73 | 0.93 | 0.94 | 1.00 | 0.90 | 2.29 | 3.06 |
| Adult-Mortality Dose-Response | 1.15 | 1.61 | 0.74 | 0.77 | 0.83 | 0.72 | 2.00 | 3.04 |
| Infant Mortality Dose-Response | 1.29 | 1.79 | 0.93 | 0.94 | 1.00 | 0.90 | 2.29 | 3.07 |
| Mortality Valuation | 1.05 | 1.35 | 0.60 | 0.62 | 0.70 | 0.55 | 1.94 | 2.97 |

(Input parameter distributions are lognormal)

Arithmetic Coefficient of Variation $\left(\frac{\sigma}{\mu}\right)$.

Table 4:
Percentile Intervals with Selected Parameters Modeled Deterministically.

| Facility | IN | | DE | | NY | | TX | |
|---|---|---|---|---|---|---|---|---|
| Deterministic Parameter | $SO_2$ | $PM_{2.5}$ | $SO_2$ | $PM_{2.5}$ | $SO_2$ | $PM_{2.5}$ | $SO_2$ | $PM_{2.5}$ |
| All Uncertain | 4,300 (650, 12660) | 4,810 (620, 15,080) | 7,660 (1,550, 20,990) | 10,250 (2,030, 28,160) | 5,160 (1,000, 14,090) | 17,790 (3,780, 47,930) | 2,400 (184, 8,250) | 2,680 (200, 8,640) |
| Air Quality Model | 4,210 (1,690, 8,860) | 4,870 (1,080, 12,800) | 7,650 (1,660, 20,260) | 10,330 (2,250, 27,320) | 5,160 (1,140, 13,630) | 17,820 (3,890, 47,090) | 2,430 (540, 6,370) | 2,700 (600, 7,040) |
| Adult-Mortality Dose-Response | 4,260 (870, 11,540) | 4,770 (800, 13,700) | 7,550 (2,180, 17,860) | 10,120 (2,790, 24,390) | 5,100 (1,400, 12,280) | 17,570 (5,180, 40,920) | 2,380 (230, 7,810) | 2,680 (250, 8,480) |
| Mortality Valuation | 4,290 (1,160, 10,720) | 4,800 (1,090, 12,620) | 7,630 (3,010, 15,590) | 10,230 (3,840, 21,760) | 5,140 (1,950, 10,790) | 17,690 (7,300, 35,320) | 2,370 (300, 7,700) | 2,690 (330, 8,170) |

(Input parameter distributions are lognormal)
Mean Damage ($/ton/year)
(5%, 95% Percentiles)

Table 5:
The Influence of Emission Height on the
Marginal Damage Distributions.

| Facility | Ground | Source | Power | Plant |
|---|---|---|---|---|
| Deterministic Parameter | $SO_2$ | $PM_{2.5}$ | $SO_2$ | $PM_{2.5}$ |
| All Uncertain | 2.45 | 1.26 | 1.00 | 0.91 |
| Emissions | 2.44 | 1.26 | 1.00 | 0.91 |
| Air Quality Model | 0.91 | 0.92 | 0.86 | 0.87 |
| Population | 2.44 | 1.23 | 1.00 | 0.90 |
| Adult-Mortality Dose-Response | 2.06 | 1.06 | 0.83 | 0.72 |
| Infant Mortality Dose-Response | 2.44 | 1.25 | 1.00 | 0.90 |
| Mortality Valuation | 1.37 | 0.99 | 0.70 | 0.55 |

(Input parameter distributions are lognormal)

Arithmetic Coefficient of Variation $\left(\frac{\sigma}{\mu}\right)$.

Table 6:
Percentile Intervals with Selected
Parameters Modeled Deterministically:
Ground-level Source and a Power Plant in New York.

| Facility | Ground Source | | Power Plant | |
|---|---|---|---|---|
| Deterministic Parameter | SO$_2$ | PM$_{2.5}$ | SO$_2$ | PM$_{2.5}$ |
| All Uncertain | 44,060 (6,940, 128,890) | 212,080 (35,956, 611,017) | 5,160 (1,000, 14,090) | 17,790 (3,780, 47,930) |
| Air Quality Model | 43,170 (9,036, 115,790) | 212,000 (44,224, 568,192) | 5,160 (1,140, 13,630) | 17,820 (3,890, 47,090) |
| Adult-Mortality Dose-Response | 42,830 (9,623, 112,820) | 206,560 (50,490, 519,840) | 5,100 (1,400, 12,280) | 17,570 (5,180, 40,920) |
| Mortality Valuation | 43,460 (12,820, 106,140) | 211,650 (66,670, 494,880) | 5,140 (1,950, 10,790) | 17,690 (7,300, 35,320) |

(Input parameter distributions are lognormal)
Mean Damage ($/ton/year)
(5%, 95% Percentiles)

Figure 1: Integrated Assessment Model Structure.
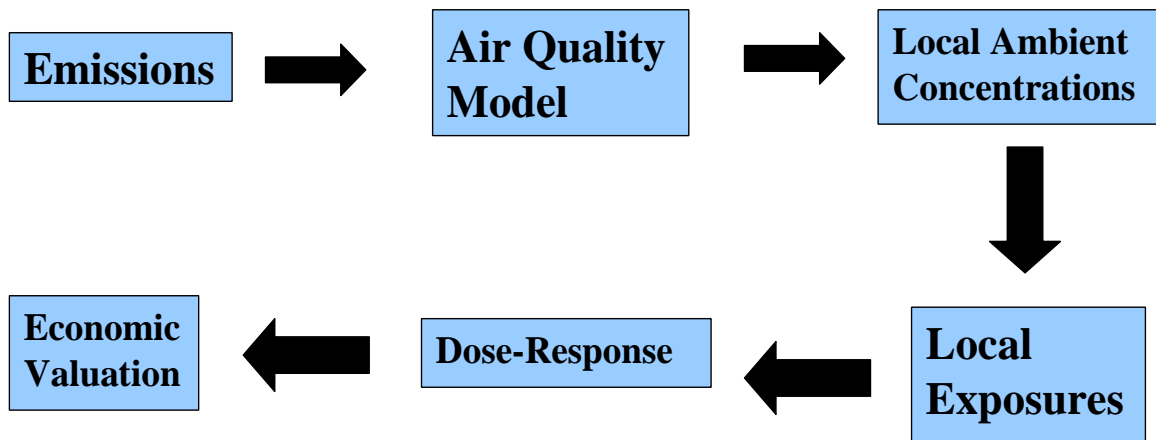
Figure 2: Distribution of SO$_2$ Marginal Damages at Four Power Plants
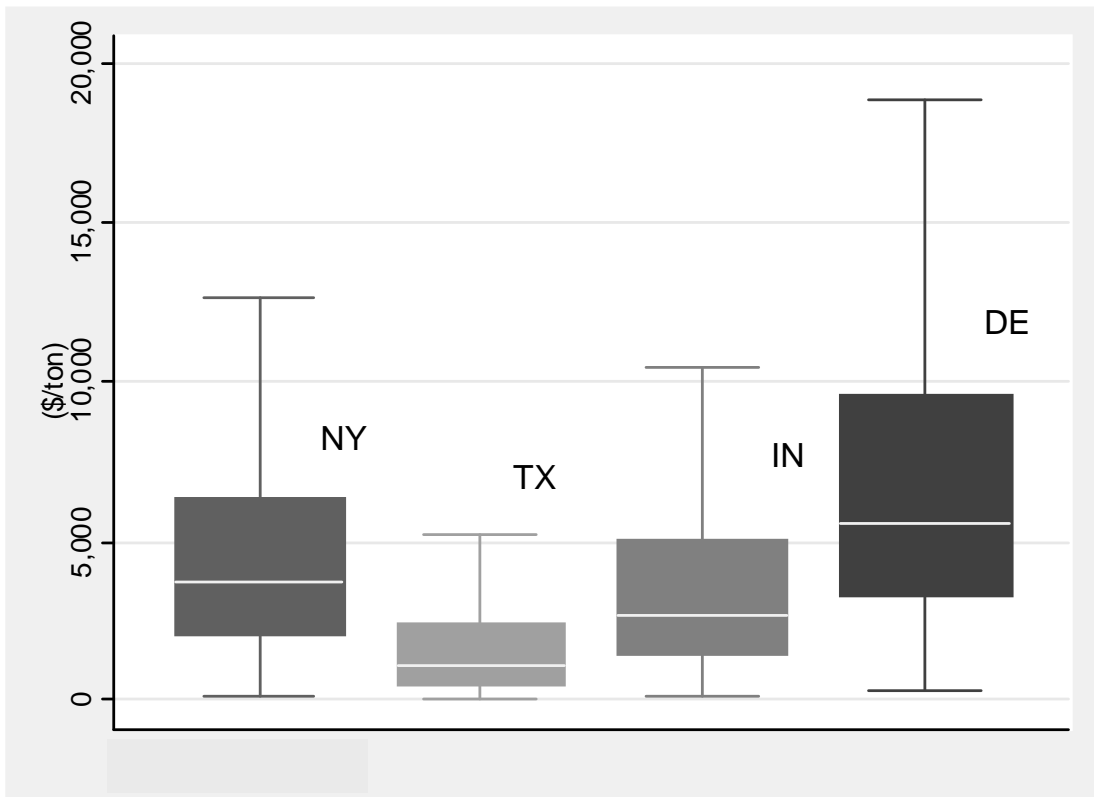
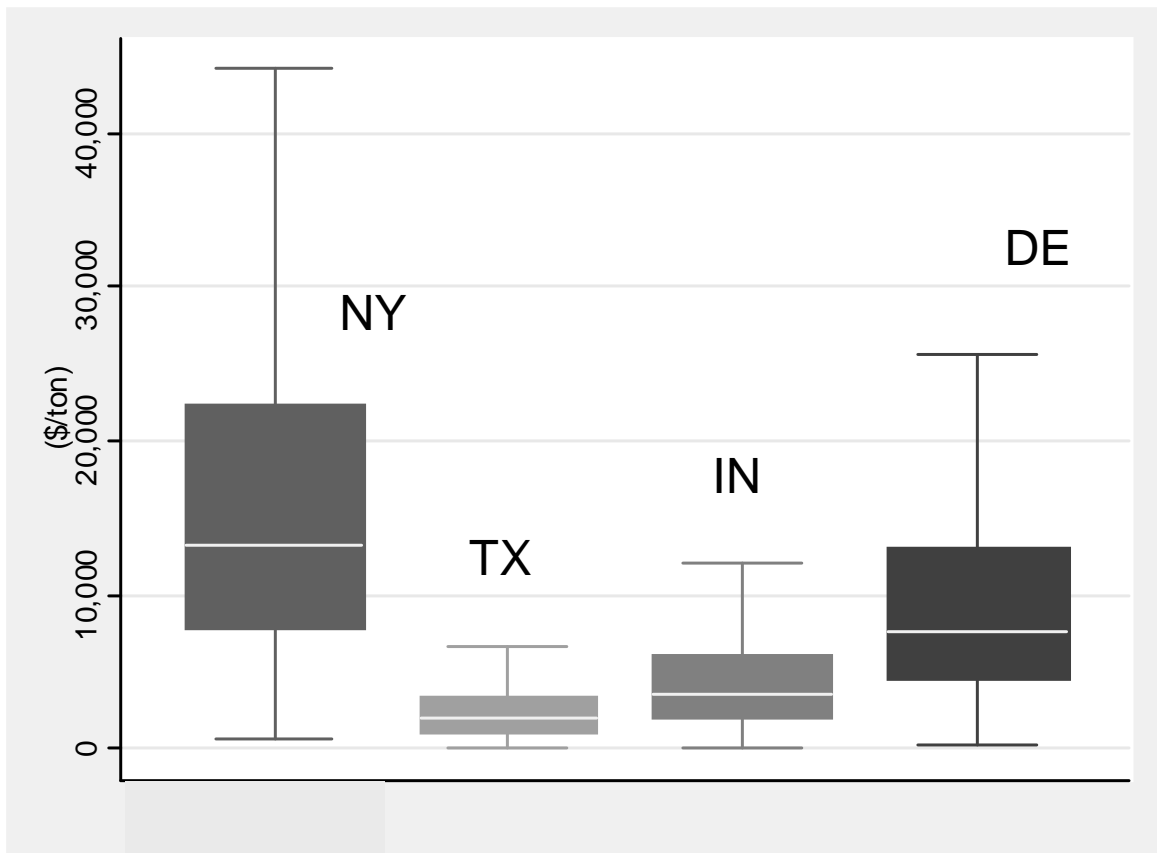Figure 3: Distributions for PM$_{2.5}$ Marginal Damages at Four Power Plants

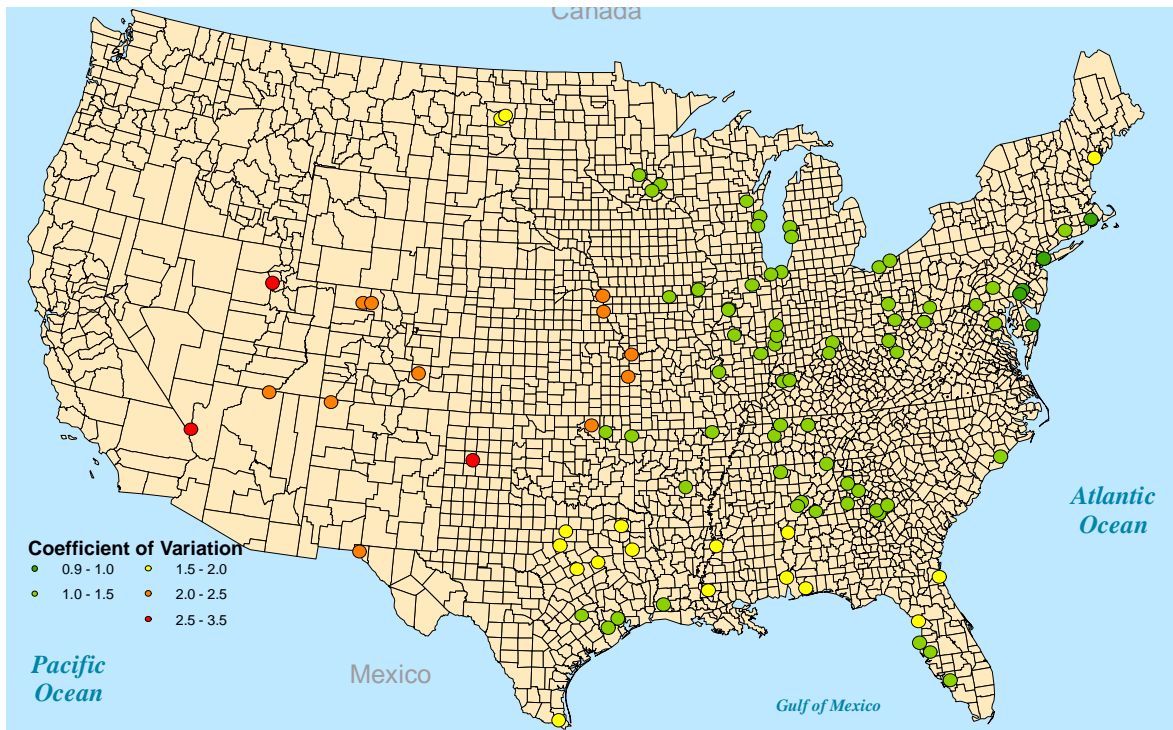Figure 4: Variability in Marginal Damage Estimates for $SO_2$.
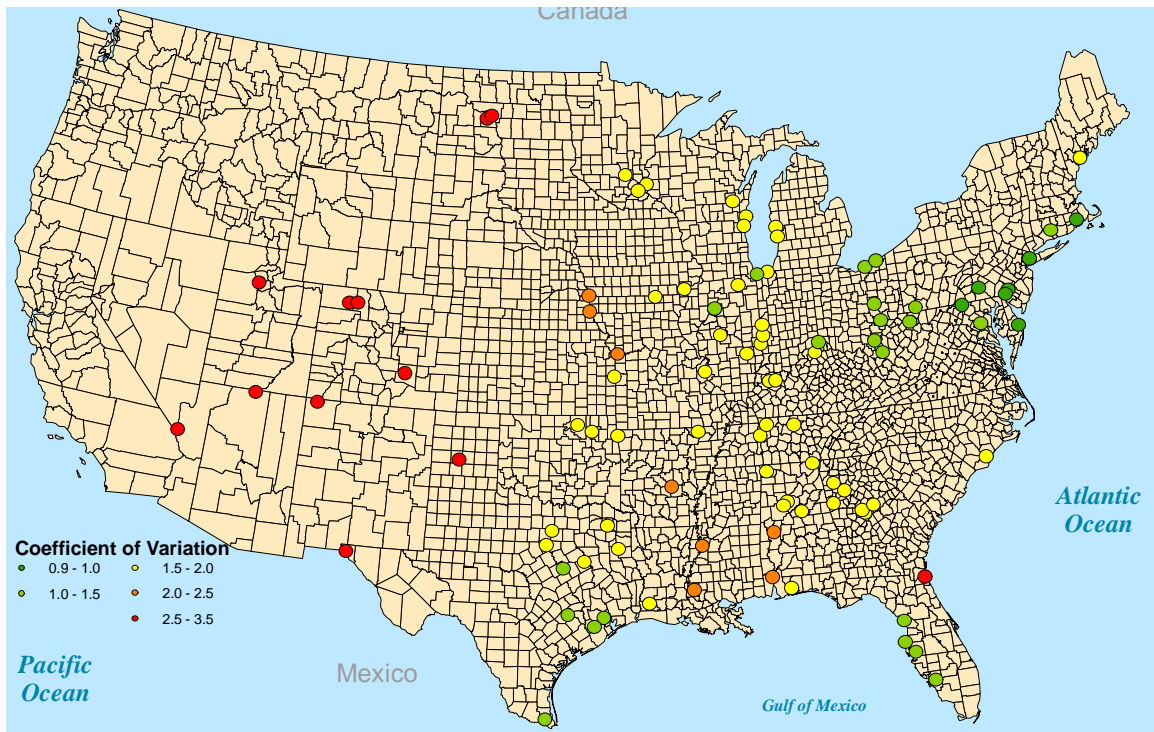
Figure 5: Variability in Marginal Damage Estimates for PM$_{2.5}$.

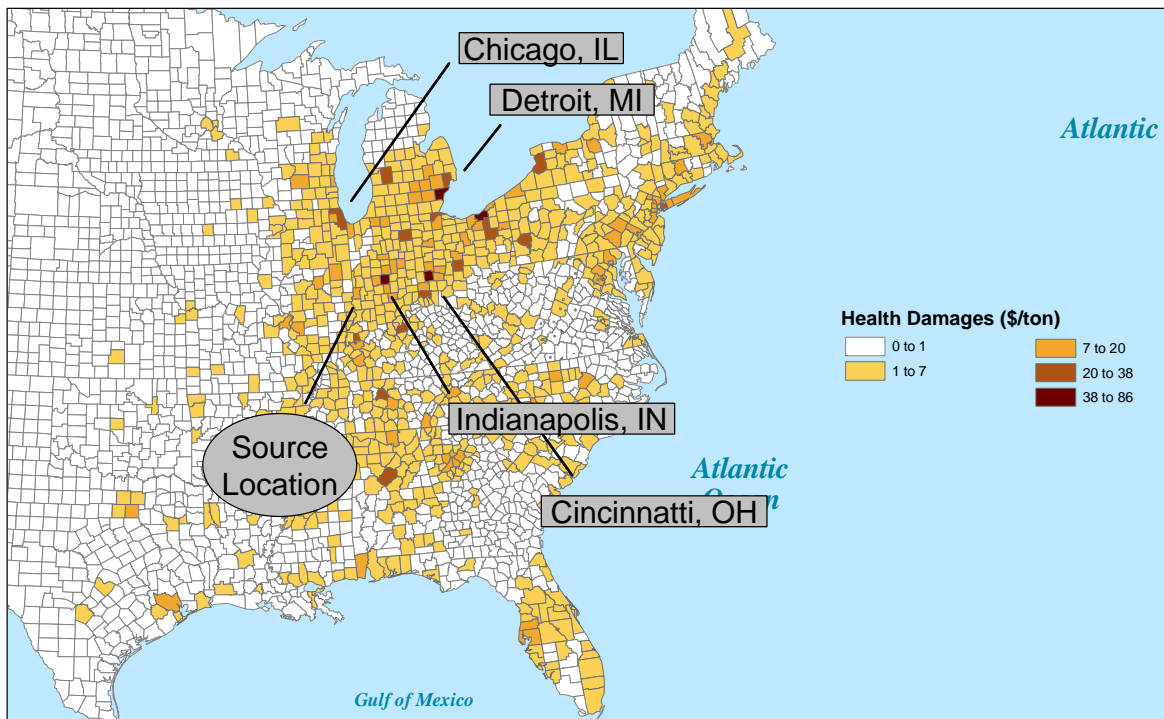Figure 6: Health Damages from $SO_2$ Emission: Mean Realization.

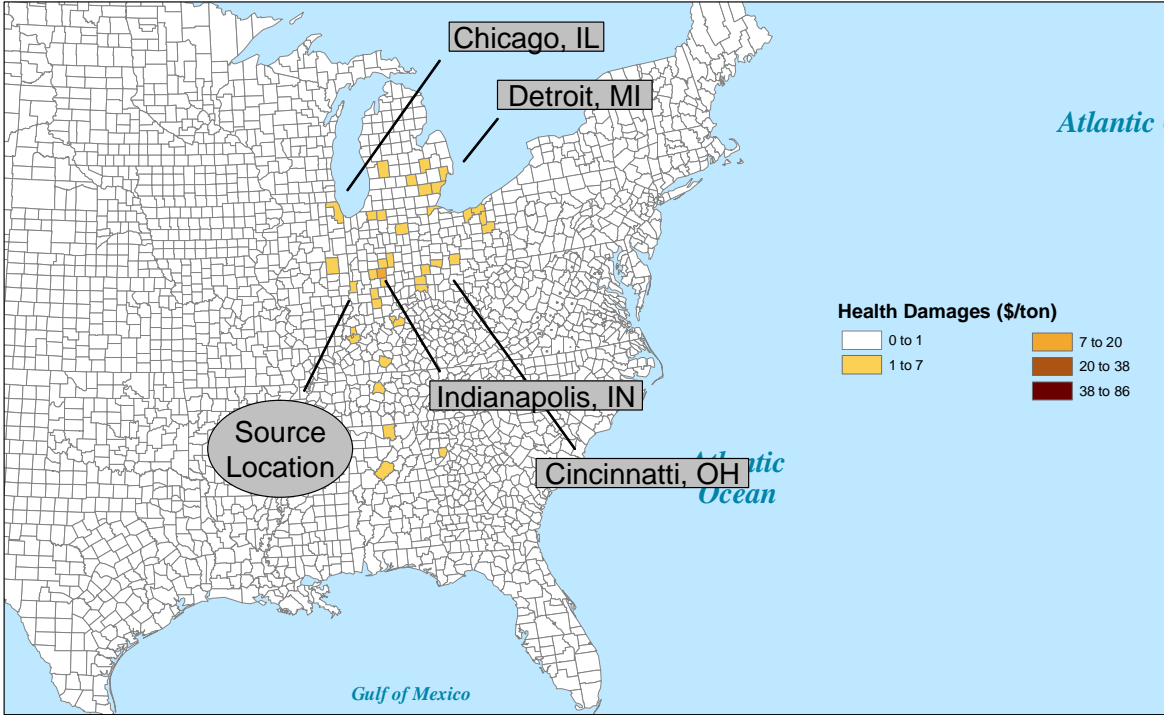Figure 7: Health Damages from $SO_2$ Emission: $1^{st}$ Percentile Realization.
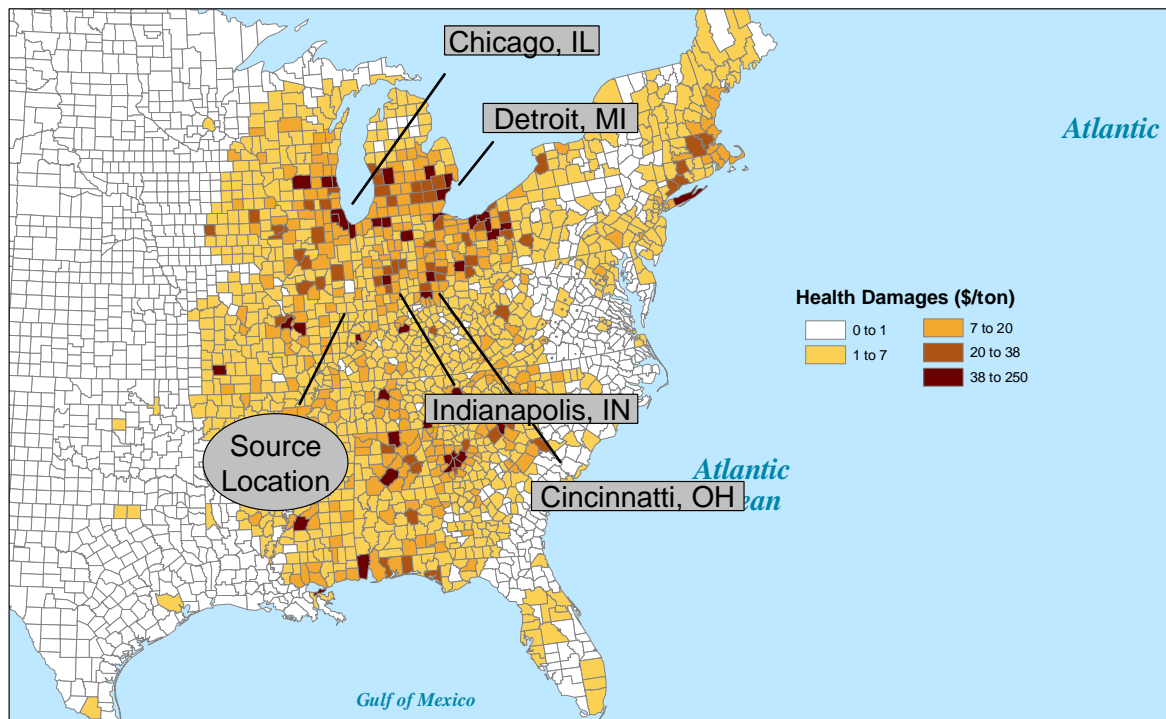
Figure 8: Health Damages from $SO_2$ Emission: $99^{th}$ Percentile Realization.

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**Characterizing Uncertainty in Air Pollution Damage Estimates.**

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# 1 Appendix

This appendix includes more detailed descriptions of the methods used to construct the distributions for the input parameters. The APEEP model constructs both normal and lognormal distributions around the five input parameters in the model. The distributions each consist of 10,000 observations with the mean and the standard deviations for each input parameter obtained from the peer-reviewed literature (see table 1 below). The model then executes a Monte Carlo procedure that entails taking a random draw from these distributions at each stage of the model, and using APEEP to calculate damages conditional on the random draws. The following sections discuss the procedures used to construct the input parameter distributions.

## 1.1 Emissions

APEEP employs 95% confidence intervals of $\pm$ 5% of the mean for $SO_2$ and $PM_{2.5}$ emissions. This value, taken from Kuykendal, et al. (2006), is slightly larger than the value reported in Abdel-Aziz and Frey (2004) who report a range for the precision of emission estimates to be $\pm$ 3%. The USEPA's reported emissions are taken as the mean value, and APEEP creates a distribution for each of the power plants in the model according to its reported mean and estimated numerical standard deviation. Further, when modeling uncertainty in emissions, we assume that the uncertainty applies to all fossil fuel power plants, rather than assuming only the power plant whose marginal damage is being calculated is uncertain. This approach is chosen because the uncertainty in emissions estimates stems from a method of measurement of emissions, rather than idiosyncratic errors in measurement at one source. This would apply to all sources whose emissions are measured using this method.

## 1.2 AQM

The empirically estimated standard errors for the $T_{s,j,r}$ estimated using the regression-based procedure discussed in section 2. are incorporated into APEEP in the following manner. The estimated standard errors are used to construct both normal and lognormal distributions around the mean $T_{j,s,r,d}$ (in the deterministic source-receptor matrices in APEEP) using a similar approach to that used in the emissions module; we create a distribution of 10,000 values for each deterministic transfer coefficient based on the estimated standard error corresponding to the distance (d) between (j) and (r), and the pollutant species. The APEEP model determines which distance category each of the transfer coefficients in the source-receptor matrix belongs to and applies the appropriate distribution derived from the appropriate standard error estimate. For each iteration of the Monte Carlo procedure, one value from the distribution of each $T_{j,s,r}$ is drawn. The estimated standard errors resulting from the bootstrap and regression procedures are shown in table 2 below.

### 1.3 Population

We use the estimated uncertainty in population projections from Stoto (1983) to create unique distributions, consisting of 10,000 observations, for each age group in each receptor county. This is done by first deriving the coefficient of variation corresponding to the Stoto study, which is then used to solve for the numerical standard deviations for the population distributions of each age group in each receptor county. The county and age-specific population estimates reported by the U.S. Census are treated as the means for the new distributions. Both normal and lognormal distributions are created. Stoto (1983) reports a coefficient of variation of 0.10.

### 1.4 Dose-Response

The dose-response relationship assumes the following functional form for premature mortalities among both adults and infants:

$$R_{s,i,t,k} = \sum_r P_{r,i,t} \times MR_{i,r} \times \left(\exp^{(\beta_{i,k}^s PM_{2.5r})} - 1\right). \tag{1}$$

where $R_{s,i,t,k}$ represents the response in terms of health state (k = mortality) due to exposure to pollutant (s) among age cohort (i) at time (t), $P_{r,i,t}$ is the population of age-cohort (i) in county (r) at time (t), $MR_{i,r}$ is the baseline mortality rate for age cohort (i) in county (r), $PM_{2.5r}$ denotes the ambient $PM_{2.5}$ levels in receptor county (r)[1], and $\beta_{i,k}^s$ represents dose-response coefficient estimated in epidemiological study for pollutants (s) and age group (i) for health state (k) which in this case corresponds to mortality rate impacts. The uncertainty in the dose-response module is associated with $\beta_{i,k}^s$, the parameter that relates changes in ambient pollution into changes in age-specific mortality rates. The public health studies that report estimates of ($\beta_{i,k}^s$) also report the estimated standard error associated with ($\beta_{i,k}^s$). We derive distributions around using the reported standard errors reported in Woodruff, Parker, and Schoendorf (2006), for infant mortalities, and Pope, et al., (2002) for adult mortalities.

### 1.5 Valuation

The valuation parameter for premature mortality and its associated uncertainty is derived directly from a meta-analysis of roughly 30 studies reported by the USEPA (USEPA, 1999). We use the reported mean and standard error for the valuation parameter to construct both a normal and a lognormal distribution of 10,000 observations around the reported mean estimate.

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[1] Recall that APEEP tracks the impact of emissions of both $SO_2$ and $PM_{2.5}$ on ambient $PM_{2.5}$ levels.

Table 1:

Empirical Estimates of Uncertainty for Input Parameters

| Input Parameter | Author, Date | Model Uncertainty |
|---|---|---|
| Emission | Kuykendahl, 2006 | 95% CI = ±5% mean |
| AQM | | See table A2 |
| Population | Stoto, 1983 | Coefficient of Var. = 0.10 |
| Dose-Response | Pope et al., 2002 | Std. dev. = 0.004 |
| Valuation | USEPA, 1999 | Std dev. = $3.2 million |

Table 2:
Air Quality Model Bootstrap Procedure Results:
$T_{s,j,r,d}$, bootstrap se's in parenthesis.

| Source Type | Distance Category | $SO_2$ | $PM_{2.5}$ | $SO_2$ $(\mu/\sigma)$ | $PM_{2.5}$ $(\mu/\sigma)$ |
|---|---|---|---|---|---|
| Ground Source | 0-100 | 4.37 e -06 (1.121 e -05) | 6.64 e -05 (2.005 e -04) | 0.3 | 3.0 |
| Power Plant | | 1.13 e -07 (1.698 e -07) | 5.20 e -07 (1.180 e -06) | 1.5 | 2.3 |
| Ground Source | 100-500 | 2.17 e -07 (1.827 e -07) | 1.05 e -06 (1.245 e -06) | 0.8 | 1.2 |
| Power Plant | | 1.23 e -07 (1.708 e -07) | 5.62 e - 07 (1.400 e -06) | 1.4 | 2.5 |
| Ground Source | 500-1000 | 7.20 e -08 (6.278 e -08) | 2.25 e -07 (2.093 e -07) | 0.9 | 0.9 |
| Power Plant | | 1.02 e -07 (1.582 e -07) | 5.05 e -07 (1.390 e -06) | 1.6 | 2.8 |
| Ground Source | 1000-3000 | 2.09 e -08 (2.960 e -08) | 5.98 e -08 (8.343 e -08) | 1.4 | 1.4 |
| Power Plant | | 8.60 e -08 (1.634 e -07) | 3.96 e -07 (1.240 e -06) | 1.9 | 3.1 |

Table 3:
Empirical Distributions of Marginal Damages.

| Facility Location | IN | | DE | |
|---|---|---|---|---|
| Input Parameter Distribution | $SO_2$ | $PM_{2.5}$ | $SO_2$ | $PM_{2.5}$ |
| Log-Normal | 4,300 | 4,810 | 7,660 | 10,250 |
| | (650, | (620, | (1,550, | (2,030, |
| | 12,660) | 15,080) | 20990) | 28,160) |
| Normal | 4,350 | 4,910 | 7,710 | 10,400 |
| | (-220, | (-320, | (-470, | (-650, |
| | 13,330) | 12,700) | 21,100) | 27,110) |

Values expressed in \$/ton/year.
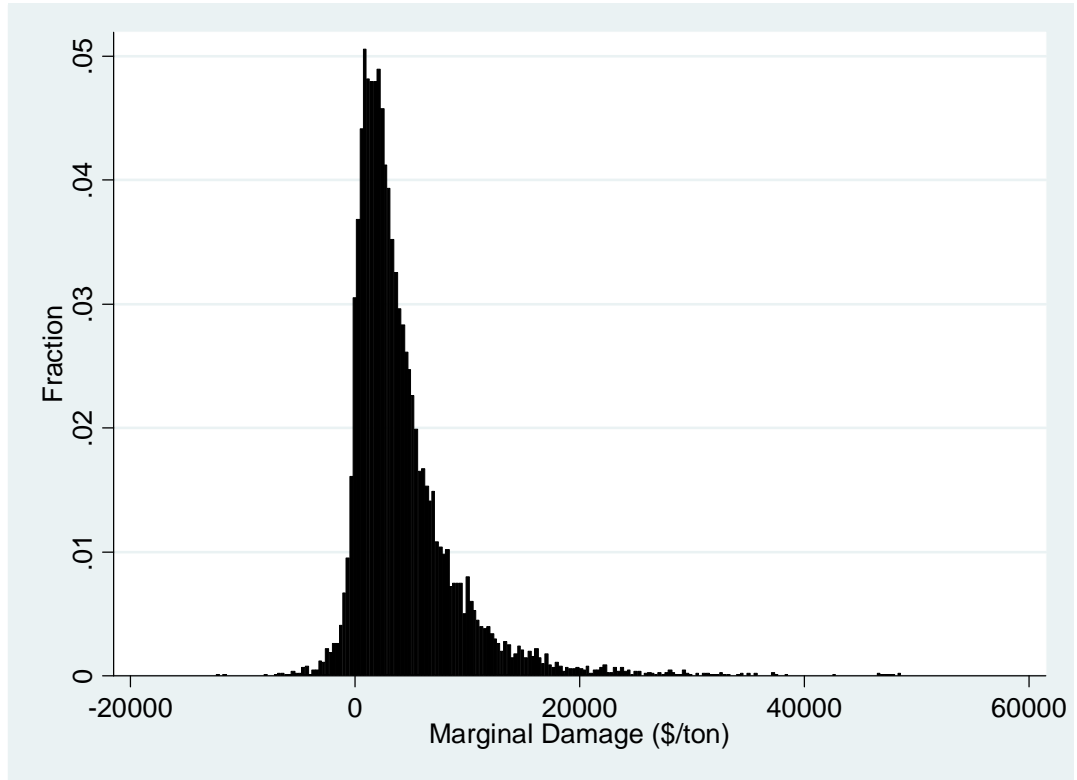$5^{th}$, $95^{th}$ percentiles in parenthesis.

Figure 1: Empirical Distribution of $SO_2$ Marginal Damage, Indiana power Plant.
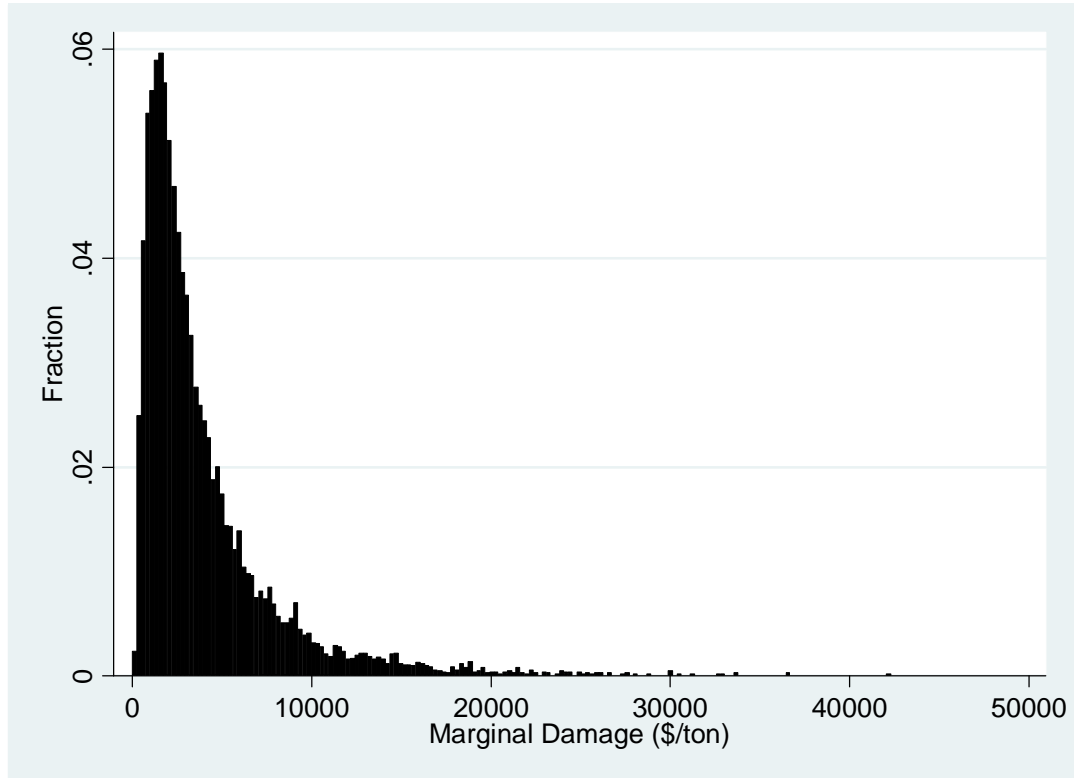


Input parameter distributions are lognormal (n = 10,000).

Figure 2: Empirical Distribution of $SO_2$ Marginal Damage, Indiana Power Plant



Input parameter distributions are normal (n = 10,000).

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