IEc

Uncertainty Analyses to Support the Second Section 812 Benefit-Cost Analysis of the Clean Air Act

Final Report - March 2011

prepared for:

James DeMocker

Office of Air and Radiation

US Environmental Protection Agency

prepared by:

Industrial Economics, Incorporated

2067 Massachusetts Avenue

Cambridge, MA 02140

617/354-0074

TABLE OF CONTENTS

CHAPTER 1 | INTRODUCTION

Section 812 of the Clean Air Act Amendments of 1990 (CAAA) established a requirement that the U.S. Environmental Protection Agency (EPA) develop periodic reports that estimate the benefits and costs of the Clean Air Act (CAA). The first analysis conducted was a retrospective analysis, addressing the original CAA and covering the period 1970 to 1990. The retrospective analysis was completed in 1997. The second Section 812 report was completed in 1999 and addressed the incremental costs and benefits of the CAAA. This first prospective analysis covered implementation of the CAAA over the period 1990 to 2010.

EPA's Office of Air and Radiation (OAR) began work on the second prospective with the drafting of an analytical plan for the study. This analytical plan was reviewed by a statutorily-mandated outside peer review group, the Advisory Council for Clean Air Compliance Analysis (Council), and the Council provided comments, which have been incorporated into the technical analysis planning. This report explores and provides some perspective on uncertainties associated with the benefits and costs estimated for the second prospective section 812 analysis.

1.1 PURPOSE AND SCOPE

The second prospective analysis of the CAA provides a comprehensive economic analysis of air regulations using the best available methods and data. Nonetheless, as with any complex policy analysis, the costs and benefits generated by this analysis are estimated with uncertainty. This uncertainty reflects an array of issues: data and model limitations, measurement error, and the various modeling assumptions and choices necessary to implement such a sophisticated and large-scale analysis. The identification and appropriate characterization of these uncertainties is an integral part of the second prospective analysis because it provides appropriate context for the results, highlights key limitations of the current analysis, and helps readers to understand the potential impact of alternative analytical choices on benefits and costs.

This uncertainty analysis reflects some significant new efforts on the part of EPA to more rigorously investigate and in some cases quantify an array of factors that contribute to uncertainty. Most of these analyses focus on key uncertainties in the estimation and monetization of avoided mortality benefits, which is appropriate given they represent a majority of the monetized benefits estimates associated with the CAAA. These analyses include a more expansive analysis of particulate matter (PM)-mortality concentration-response (C-R), alternative means of modeling mortality risk changes and how they are realized over time, and the sensitivity of monetized benefits to the choice of alternative distributions for the metric used to value avoided mortalities, the value of statistical life (VSL). This study also includes updated assessments of uncertainties in the "upstream" analytical elements of emission estimation and air quality modeling, an analysis of uncertainties in visibility benefits of the CAAA, and targeted cost uncertainty analyses addressing the impacts of key analytical assumptions on cost projections.

Conducting a comprehensive uncertainty analysis for a national-scale study with a scope as expansive as the Section 812 Benefit-Cost Analysis is a challenging task. The complexity of the air quality modeling system used in the analysis, and the time and resources needed to run it, make it impractical to employ simulation techniques that use statistical sampling to analyze the impact of upstream uncertainties in emissions and air quality modeling inputs on the criteria pollutant concentration outputs. Both the National Research Council (NRC) in its 2002 report evaluating EPA's air quality benefits analysis procedures and the EPA Science Advisory Board's Advisory Council on Clean Air Compliance Analysis (the Council) in numerous advisories have encouraged more comprehensive analysis of uncertainties in benefits analyses for air quality regulations.[1] While the NRC report presents ambitious and laudable long-tem goals for Agency analysis, the data and methodologies required to meet many of these goals are not available for application in the current 812 analysis.

To make progress toward improved treatment of analytical uncertainty, the 812 Project Team (the Project Team) pursued a more incremental strategy in the second 812 prospective, guided by four objectives that we shared with the Council in 2007:

- Identify reasonable incremental advances in uncertainty analysis suitable for application within a complex national-scale study;
- Conduct sensitivity analyses that provide policy-relevant insights concerning impacts of alternative assumptions on benefit and cost estimates for the CAA;
- Where appropriate, incorporate EPA's latest tools and data for uncertainty analysis (e.g. the PM mortality expert elicitation, EPA's Response Surface Model (RSM) for PM); and
- Enhance presentation of results and uncertainty through the use of graphics to complement tabular summaries.

Before providing an overview of the Project Team's approach to uncertainty analysis, we review the approach taken in the First Prospective Study.

[1] National Research Council (2002). *Estimating the Public Health Benefits of Proposed Air Pollution Regulations*. National Academies Press, Washington ,D.C.

1.2 OVERVIEW OF UNCERTAINTY ANALYSIS APPROACH IN THE FIRST PROSPECTIVE

EPA made use of four methods for characterizing uncertainty in the first prospective: probabilistic modeling; sensitivity tests; alternative paradigms; and qualitative characterizations.

1.2.1 PROBABILISTIC MODELING

In the first prospective, the Project Team used probabilistic analysis to model uncertainty in the human health effects of criteria pollutants and in the economic valuation of human health effects. For example, the VSL input was based on analysis of results of 26 mortality risk valuation studies. In order to characterize uncertainty in this important input parameter, we used the "discrete distribution of the best available estimates [i.e., the 26 studies] as a basis for quantitatively characterizing the probability of alternative values."

The probabilistic approach in the first prospective was limited in scope to those portions of the analysis where the Project Team could readily generate probabilistic characterizations of uncertainty - this included the C-R and valuation steps. In addition, the quantitative characterizations largely reflected measurement uncertainty and cross-study variability in those steps, and did not extend to model or paradigm uncertainty. The scope of the quantitative results also did not include quantitative characterizations of uncertainty in emissions, air quality modeling, or cost estimates.

1.2.2 ALTERNATIVE PARADIGMS

The Project Team used the alternative paradigms approach in the first prospective to examine the impact of several key methodological choices, including: the choice to use a statistical life approach, rather than a statistical life years approach, to estimate the economic benefits of reduced mortality; the choice of a single study to characterize the relationship between PM exposure and premature mortality; and the choice to omit several quantifiable but less well-supported categories of environmental benefits (e.g., residential visibility). Ideally, we would have liked to examine these model choices using some sort of probabilistic analysis. Short of an expert elicitation approach, however, we found no reliable means to assess the relative likelihood of these model choices being “correct.” As a result, the direction and magnitude of the uncertainty in these model choices was considered by examining the effects of employing alternative paradigms or models.

1.2.3 SENSITIVITY TESTS

The Project Team applied sensitivity analysis in a number of different sections of the first prospective. One of the most prominent examples was in the cost estimates, where sensitivity analysis was used to evaluate the effect of altering certain key input parameters. Sensitivity tests were used to examine the impact of key assumptions and data limitations on estimates of direct costs of six major cost-driving provisions, and qualitative characterizations were used to examine the potential impact of other factors on the overall uncertainty in cost estimates. The six provisions were: California Reformulated Gasoline, PM National Ambient Air Quality Standards (NAAQS) controls, the Low Emissions Vehicle (LEV) program (the National and California programs combined), Non-utility Stationary Source NOx controls, and the Tailpipe/Extended Useful Life standard. In each of these sections, we found it difficult to assign a quantitative distribution to some of the input parameters, in part because resource and time limitations precluded even informal expert elicitation of variability and uncertainty. Although this approach enabled us to characterize some of the important but uncertain inputs to the cost estimates, it did not allow us to describe either the likelihood of obtaining a given result or the probability distribution of results.

Sensitivity tests were also used to examine the effect of different assumptions regarding the discount rate. The analysis found that changes in the discount rate had only a small effect on annual cost and benefit estimates. Although changes in the discount rate had a larger effect on the net present value calculations, and a substantial effect on the Title VI results, the study's central conclusion that the benefits of the CAA exceed its costs remained robust to alternative discount rate assumptions.

Sensitivity analyses were also conducted to evaluate the potential effect of a threshold in the PM-mortality relationship, and the effect of introducing a new procedure for estimating changes in willingness-to-pay (WTP) as individual real income changes over time. Both of these sensitivity tests were confined to appendices in the First Prospective. The income elasticity adjustment, however, is now standard practice for primary benefits estimation throughout the Agency, with sensitivity analyses using alternative estimates of the income elasticity also being conducted in many of the Agency's benefits analyses.

1.2.4 QUALITATIVE APPROACHES

Qualitative approaches to characterizing uncertainty were used in virtually every component of the first prospective, in an effort to be comprehensive in the identification of sources of uncertainty. They were used in the summaries of uncertainty in the cost analysis to examine the uncertainty associated with learning curves and tax-interaction effects and also to examine uncertainty regarding model specification. In addition, qualitative tables were used extensively in the benefits analysis. For example, while it was impractical to quantitatively model uncertainty in the emissions estimation and air quality modeling components of the analysis, several specific uncertainties in these steps were assessed qualitatively, with estimates of the direction and magnitude of the uncertainty (e.g., the effect of incomplete characterizations of direct PM and precursor emissions composition). Qualitative tables were also used in the first prospective to characterize uncertainty in the valuation of ecological benefits. Appendix A presents the qualitative uncertainty summary tables from the first prospective Report to Congress.

1.3 OVERVIEW OF UNCERTAINTY ANALYSIS PLAN FOR SECOND PROSPECTIVE

Exhibit 1-1 illustrates the Project Team's approach to uncertainty analysis in the second prospective Section 812 study. The grey box represents the extent of uncertainty analysis in the first section 812 prospective analysis. As noted above the modifications employed in the current analysis included both "online" analyses (shown in color), that feed information on uncertainty into the analytical chain at various points and propagate it through the remaining steps in the chain, and separate "offline" analyses and research that will provide insights into the uncertainty, sensitivity, and robustness of results to alternative assumptions that are currently most easily modeled outside the main analytical process.

The online analyses consist of the selection of alternative inputs for mortality C-R and valuation in BenMAP, as well as a "modified" online analysis of the effect on benefits of sector specific, marginal changes in PM-related emissions from the core scenarios. This modified online analysis substitutes EPA's RSM for CMAQ, a less resource intensive meta-model of CMAQ used to rapidly approximate PM concentrations.

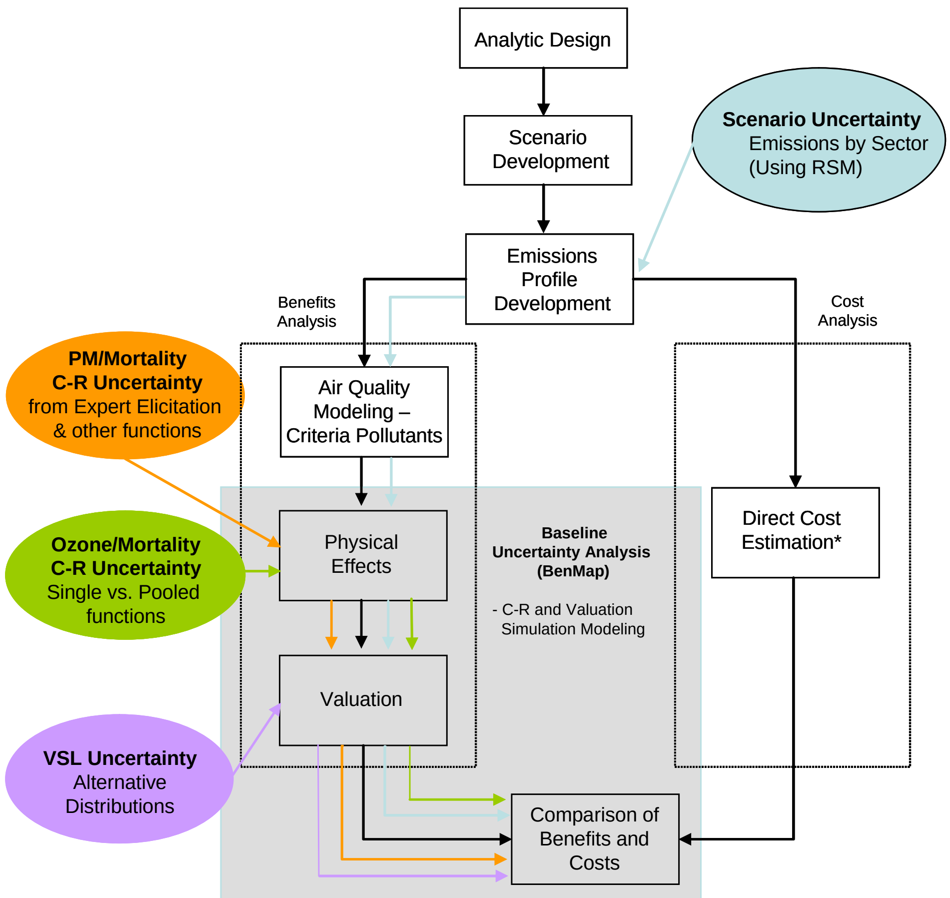
The bottom box in Exhibit 1-1 lists additional offline research and analysis that we incorporated into the current 812 study, and Exhibit 1-2 provides additional information on each analysis. As with the online analyses, these analyses were chosen because they address uncertainty in key analytical elements or choices that may significantly influence benefit or cost estimates. Also, as in the first prospective, each analytical element (starting with emissions profile development) features a comprehensive qualitative evaluation of key uncertainties, presented in Appendix C of this report.

1.4 RELATIONSHIP OF THIS DOCUMENT TO OTHER SECOND PROSPECTIVE ANALYSES

This report describes the analyses conducted by the Project Team to assess and characterize uncertainty in the estimated benefits and costs of the CAAA presented in the full integrated report. The analyses are designed to assess these uncertainties typically by re-running benefit or cost analyses, changing specific model parameters, employing alternative scenarios or varying key assumptions, and even substituting alternative models. As such, the benefit and cost estimates presented in this report rely on results generated in prior analytic components of the second prospective study. As illustrated in Exhibit 1-1, EPA conducted both emissions estimation and air quality modeling analyses to generate data that underlies the benefits estimation approaches. EPA plans to make full reports on each of these major analytic steps available to the public online at the project website, www.epa.gov/oar/sect812.

The results presented in this report do not represent EPA's primary benefits or costs, except where such results are presented (and identified as such) for the purposes of comparison to alternative estimates. EPA's primary benefits estimates are based on EPA's preferred set of analytic assumptions, models, and data sources, many of which have been explicitly reviewed by the Council over the course of many years and have been embodied in standard benefits estimation practice as carried out by EPA's Office of Air and Radiation in Regulatory Impact Analyses. Details surrounding the methods used to derive the primary benefit and costs results are described in separate reports, *Benefits Analyses to Support the Second Section 812 Prospective Benefit-Cost Analysis of the Clean Air Act*, and *Cost Analyses to Support the Second Section 812 Prospective Benefit-Cost Analysis of the Clean Air Act*.

EXHIBIT 1-1. UNCERTAINTY ANALYSIS PLAN FOR SECOND PROSPECTIVE SECTION 812 BENEFIT COST ANALYSIS OF THE CLEAN AIR ACT AMENDMENTS OF 1990



Offline Analyses

1. Dynamic versus Static Population Modeling (Benefits)
2. Cessation lag (Benefits)
3. Differential Toxicity of PM Components (Benefits)
4. Emissions and Air Quality Modeling Uncertainty Literature Review and Qualitative Analysis (Benefits)
5. Unidentified Controls (Costs)
6. Fleet Composition, I&M Failure Rates (Costs)
7. Learning Curve Assumptions (Costs)

* In addition, we perform a computable general equilibrium (CGE) analysis of costs alone and of costs and benefits, but we omit this step from the diagram because we do not conduct uncertainty analyses on the CGE modeling.

EXHIBIT 1-2. "OFFLINE" UNCERTAINTY ANALYSES

ISSUE	APPROACH	ANALYTICAL ELEMENTS AFFECTED	OUTPUT
Emissions/Air Quality Parameter Uncertainty	Identification of key factors through extensive literature review	Emissions and air quality modeling	Characterization of current state of knowledge concerning uncertainty assessment for large-scale air quality modeling applications.
Emissions Scenario Uncertainty	Model effects on benefits of incremental changes to emissions from individual emissions sectors.	Benefits side elements (PM only)	Dollar per ton estimates of marginal benefits from incremental changes in each of the major emitting sectors in 2010 and 2020.
Emissions Scenario Uncertainty	Examine effects of alternative modeling of emissions in 2000 from EGU sources. Use continuous emissions monitoring (CEM) data instead of IPM results, coupled with alternative counterfactual consistent with CEM approach.	Benefits side elements (PM only)	Alternative year 2000 benefit results for comparison with output from IPM-based results from main analysis.
Benefits "Cessation Lag"	As a post-processing step to BenMAP, apply alternative approaches to describe how mortality risk in a population changes over time following a reduction in air pollution, as the population moves from its initial steady-state risk level to its new level (all other factors being held constant).	Benefits side elements (PM mortality only)	Alternative net present value results for avoided premature mortality due to PM reductions in 2000, 2010, and 2020.
Dynamic Population Modeling	Evaluate the impact of estimating benefits using a dynamic rather than static population modeling approach, by applying a life-table based air quality risk assessment tool.	Benefits side elements (PM mortality only)	Changes in numbers of deaths per year, life years gained, and changes in period conditional life expectancy due to PM reductions in 2000, 2010, and 2020.
Differential Toxicity of PM Components	Review of feasibility and policy relevance of potential notional analysis of evidence-based alternative assumptions concerning the relative toxicity of major PM components.	Benefits side elements (PM mortality only)	Review concluded that available data do not support a policy relevant notional analysis at this time.
Unidentified Controls	Develop cost estimates using alternative assumptions about the threshold for, and cost of, applying unidentified local controls to achieve NAAQS compliance.	Direct Costs	Alternative direct cost estimates for each target year reflecting sensitivity of costs to these assumptions.

ISSUE	APPROACH	ANALYTICAL ELEMENTS AFFECTED	OUTPUT
Fleet Composition and I&M Failure Rates	Develop cost estimates for mobile source sector using alternative assumptions about 1) future fleet composition and fuel efficiency; and 2) alternative failure rates for I&M program testing.	Direct Costs	Alternative direct cost estimates for each target year reflecting sensitivity of costs to these assumptions.
Learning Curve Assumptions	Develop cost estimates using alternative assumptions about the degree to which learning effects reduce costs of pollution control over time, focusing on industries lacking published learning effect estimates in the peer-reviewed literature.	Direct Costs	Alternative direct cost estimates for each target year reflecting sensitivity of costs to these assumptions.
Unquantified Uncertainties	Comprehensive qualitative uncertainty analysis	All	Summary tables describing key uncertainties and the size and direction of their likely impact on results (if known).

The Agency has prepared an integrated report for the entire project.[2] The integrated report addresses each of the major analytic components, and presents comparisons of benefits and costs for each of the target years. It also integrates the implications of uncertainty analyses that characterize confidence in these results.

1.5 ORGANIZATION OF DOCUMENT

The remainder of the document is split into eight chapters:

- **Chapter 2: Direct Cost-Related Uncertainty** – This chapter explores the uncertainty surrounding key inputs to the direct cost estimates, including local controls, composition of motor vehicle sales and fleet fuel efficiency, inspection failure rates and learning rates.
- **Chapter 3: Emissions and Air Quality Modeling Uncertainty** – This chapter describes our analysis of uncertainty in emissions estimates and air quality modeling. This includes sensitivity analyses of the emitting sector and characterizing model uncertainty in the EGU sector emissions estimation approach.
- **Chapter 4: Concentration-Response Function Uncertainty** – This chapter provides estimates of CAAA-related avoided deaths resulting from application of alternative C-R functions for both PM and ozone.

[2] U.S. Environmental Protection Agency (2011). *The Benefits and Costs of the Clean Air Act from 1990 to 2020*. Final Report, March 2011. Office of Air and Radiation.

- **Chapter 5: Differential Toxicity of PM Components** – This chapter provides our assessment of potential approaches to account for differential toxicity of PM components.
- **Chapter 6: Particulate Matter/Mortality Cessation Lag** – This chapter explores uncertainty in the assumption of the cessation lag between CAAA-related PM exposure changes and the resulting avoided mortality.
- **Chapter 7: Dynamic Population Modeling** – This chapter provides a comparison between the benefits results from BenMAP, which does not take into account previous air pollution changes, and a dynamic population simulation model which tracks the effects of air pollution changes in the U.S. population over time.
- **Chapter 8: Valuation Uncertainty** – This chapter describes our analysis of uncertainty in monetary valuation of benefits, including a presentation of estimates resulting from different assumptions of VSL and discount rates.
- **Chapter 9: Conclusions** – This chapter provides our overall conclusions about the uncertainty analyses presented in the report.

CHAPTER 2 | DIRECT COST-RELATED UNCERTAINTY

2.1 INTRODUCTION

Most of this document addresses uncertainties in the benefits of the 1990 Clean Air Act Amendments (CAAA). The Project Team also assessed various uncertainties associated with the costs of the Amendments. The key uncertainties that we examined include the following:

- ***Local Controls***: As indicated in Chapter 7 of the Second Prospective Cost Report, the Project Team used a cost cap of $15,000 per ton to estimate the costs of identified local controls and also applied a cost of $15,000 per ton to unidentified controls. To assess the sensitivity of the local controls analysis to changes in these values, we estimated the costs of local controls based on a $10,000 per ton cost cap for identified controls and a $10,000 per ton cost for unidentified controls.

- ***Composition of Motor Vehicle Sales and Fleet Fuel Efficiency***: In Chapter 3 of the Second Prospective Cost Report, the 812 Project Team estimated CAAA-related costs for the on-road sector based on projections of vehicle sales and fuel consumption derived from the Department of Energy's (DOE's) *Annual Energy Outlook 2005* (AEO 2005). To examine the sensitivity of the Project Team's on-road sector cost estimates to alternative assumptions about the composition of light-duty vehicle sales and the fuel economy of the light-duty vehicle fleet, we developed alternative cost estimates based on AEO 2008, which contains more up-to-date projections of both these variables.

- ***Inspection Failure Rates***: To estimate the repair costs associated with vehicle inspection and maintenance (I&M) programs mandated by the CAAA, the Project Team used failure rate estimates derived from 2003 and 2004 Wisconsin I&M program data. A 2001 National Research Council (NRC) report on I&M programs, however, presents failure rates much lower than those suggested by the Wisconsin data.[3] As a sensitivity analysis, we estimated the total costs of I&M programs using failure rates derived from the NRC report.

- ***Learning Rates***: Throughout the Second Prospective Cost Report, the Project Team used a series of "learning rates" to capture the extent to which costs decline

[3] Committee on Vehicle Emission Inspection and Maintenance Programs, Board on Environmental Studies and Toxicology, Transportation Research Board, National Research Council, *Evaluating Vehicle Emissions Inspection and Maintenance Programs*. 2001.

as firms gain experience with air pollution control technologies. The learning rate for a technology represents the percentage reduction in costs associated with each doubling in the cumulative production of that technology. Where possible, the Project Team used published estimates of technology- or industry-specific learning rates. For sectors and control technologies for which no empirical estimates of the learning rate were readily available, the Project Team employed a default learning rate of 10 percent based on advice provided by the EPA Science Advisory Board's Advisory Council on Clean Air Compliance Analysis.[4] To assess the extent to which this default rate influences the results of the cost analysis, we estimated the costs of the Amendments using alternative default learning rates of 5 and 20 percent.

2.2 METHODS

In the following four sections, we present our approach for analyzing each of the uncertainties described above.

2.2.1 LOCAL CONTROLS ANALYSIS

As indicated above, the Project Team's analysis of local controls assumed a $15,000 per ton cost cap for identified controls (i.e., the analysis assumed that local air quality managers would not require the implementation of controls costing more than $15,000 per ton of emissions controlled).[5] In addition, in areas where these identifiable control measures would be insufficient for attainment with the 8-hour ozone National Ambient Air Quality Standards (NAAQS), the Project Team assumed a fixed cost of $15,000 per ton for unidentified volatile organic compound (VOC) and nitrogen oxide (NO_x) controls. To assess the sensitivity of the local controls cost analysis to an alternative cost cap and an alternative fixed cost per ton for unidentified controls, we estimated the total cost of local controls based on a cost cap of $10,000 per ton for identified controls and a fixed cost of $10,000 per ton for unidentified measures.

2.2.2 COMPOSITION OF MOTOR VEHICLE SALES AND FLEET FUEL EFFICIENCY

The Project Team's analysis of the costs associated with motor vehicle tailpipe and fuel rules is based on sales and fuel efficiency projections from the 2005 version of DOE's *Annual Energy Outlook*. Since the release of AEO 2005, however, fuel prices have been more volatile than in previous years, leading many consumers to shift to more fuel efficient vehicles, and the Department of Transportation revised the Federal Corporate Average Fuel Economy (CAFE) standards. Given these developments, AEO 2008 projects that passenger cars will make up a greater portion of light-duty vehicle sales in 2010 and 2020 than is projected by AEO 2005. AEO 2008 also assumes that the light-

[4] U.S. Environmental Protection Agency Science Advisory Board, EPA-SAB-COUNCIL-ADV-07-002, "Benefits and Costs of Clean Air Act – Direct Costs and Uncertainty Analysis", Advisory Letter, June 8, 2007. Available at http://www.epa.gov/sab/pdf/council-07-002.pdf.

[5] E.H. Pechan & Associates, Inc. and Industrial Economics, Inc., *Direct Cost Estimates for the Clean Air Act Second Section 812 Prospective Analysis: Draft Report*, prepared for U.S. EPA, Office of Air and Radiation, October 31, 2008.

duty vehicle fleet will be more fuel efficient relative to the projections in AEO 2005. As indicated in Exhibit 2-1, AEO 2008 estimates that the light-duty vehicle fleet in 2020 will be nearly 15 percent more fuel efficient than was projected by AEO 2005. In addition, whereas sales projections derived from AEO 2005 suggest that passenger cars will make up 42 percent of light-duty vehicle sales in 2020, AEO 2008 suggests that passenger cars will represent 49 percent of light-duty vehicle sales in 2020.[6]

EXHIBIT 2-1. LIGHT DUTY VEHICLE FUEL EFFICIENCY, CAR SALES, AND TRUCK SALES FOR 2010 AND 2020 BASED ON AEO 2005 AND AEO 2008

	AEO 2005 (PRIMARY ESTIMATES)[A]	AEO 2008 (ALTERNATIVE ESTIMATES)[B]
FLEET AVERAGE VEHICLE FUEL EFFICIENCY (MPG)		
2010	20.14	20.30
2020	20.73	23.75
2010 LIGHT-DUTY VEHICLE SALES (THOUSANDS)		
Passenger Cars	8,417	8,542
Light-Duty Trucks	8,172	8,046
2020 LIGHT-DUTY VEHICLE SALES (THOUSANDS)		
Passenger Cars	7,377	8,548
Light-Duty Trucks	10,106	8,935

Sources:
a. Light-duty vehicle fuel efficiency values obtained from Table 47 of AEO 2005. Light-duty vehicle sales values derived from the sales data presented in Table 45 of AEO 2005 using the methodology described in Chapter 3 of E.H. Pechan & Associates, Inc. and Industrial Economics, Inc., *Direct Cost Estimates for the Clean Air Act Second Section 812 Prospective Analysis: Draft Report*, prepared for U.S. EPA, Office of Air and Radiation, October 31, 2008.
b. Light-duty vehicle fuel efficiency values obtained from Table 49 of AEO 2008. Sales estimates for passenger cars and light-duty trucks based on the primary (AEO 2005-based) estimate of total light-duty vehicle sales, re-distributed between passenger cars and light-duty trucks based on the distribution of sales between these vehicle categories presented in Table 47 of AEO 2008.

To assess the extent to which the Project Team's cost estimates for the on-road sector would change under the alternative AEO 2008 assumptions, we estimated the cost of motor vehicle tailpipe and fuel rules for both the 2010 and 2020 target years based on the AEO 2008 data.

[6] It is important to note that Exhibit 2-3 does not present the sales estimates reported in AEO 2008. Because our goal is to examine the sensitivity of the cost analysis to the *composition* of light-duty vehicle sales rather than to the total number of vehicles sold, we use the AEO 2008 data to estimate the distribution of light-duty vehicle sales between passenger cars and light-duty trucks. We then apply this distribution to the total light-duty vehicle sales estimates derived from AEO 2005.

2.2.3 VEHICLE INSPECTION FAILURE RATE

In the Second Prospective Cost Report, the Project Team's estimates of the repair costs associated with motor vehicle I&M programs employed program- and year-specific inspection failure rates derived from 2003 and 2004 data for Wisconsin I&M programs. The Wisconsin data suggested that the failure rate associated with annual dynamometer-based I&M programs is 14 percent, and the Project Team used this rate to derive failure rates for annual idle, biennial idle, and biennial dynamometer-based I&M programs. In its June 2007 review of the Draft Direct Cost Report, the Science Advisory Board Advisory Council on Clean Air Compliance Analysis (the Council) noted that a 2001 NRC report referenced a failure rate of 2.1 percent for annual dynamometer-based programs, which is approximately one-seventh the value derived from the Wisconsin data.[7]

To assess the sensitivity of the I&M cost analysis to the assumed failure rate for annual dynamometer-based programs, we developed alternative cost estimates for CAAA-mandated I&M programs based on the failure rate reported by the NRC. Because the Project Team used the estimated failure rate for annual dynamometer-based programs as a basis for estimating the failure rates for annual idle, biennial idle, and biennial dynamometer-based I&M programs, an initial step in this sensitivity analysis was re-estimation of the failure rates for these program types. We generated these values using the same approach as employed in the Second Prospective Cost Report and the 2.1 percent failure rate for annual dynamometer-based programs reported by the NRC. Exhibit 2-2 presents the adjusted failure rates for each program type and the corresponding values used in the Second Prospective Cost Report.

2.2.4 DEFAULT LEARNING RATE

In the Second Prospective Cost Report, the Project Team adjusted total program costs to account for "learning curve" impacts (i.e., the extent to which the costs of a technology decline as experience with that technology increases over time). Wherever possible, the Project Team employed technology- or industry-specific learning rates obtained from the literature. Where industry-specific learning rates were not readily available, the Council advised the Project Team to employ a default learning rate of 5 to 10 percent. Based on this advice, the Project Team applied a default rate of 10 percent to the following technologies:

- Selective non-catalytic reduction at electric generating units (EGUs) (O&M costs only);
- Activated carbon injection at EGUs;

[7] Committee on Vehicle Emission Inspection and Maintenance Programs, Board on Environmental Studies and Toxicology, Transportation Research Board, National Research Council. *Evaluating Vehicle Emissions Inspection and Maintenance Programs*. 2001.

EXHIBIT 2-2. SUMMARY OF PRIMARY AND ALTERNATIVE FAILURE RATES FOR MOTOR VEHICLE INSPECTION AND MAINTENANCE PROGRAMS

PROGRAM	FAILURE RATES (PERCENT)					
	2000		2010		2020	
	Primary Failure Rate Estimates (based on Wisconsin data)	Alternative Failure Rate Estimates (based on NRC-reported value)	Primary Failure Rate Estimates (based on Wisconsin data)	Alternative Failure Rate Estimates (based on NRC-reported value)	Primary Failure Rate Estimates (based on Wisconsin data)	Alternative Failure Rate Estimates (based on NRC-reported value)
Annual Idle	7.00	1.05	13.09	1.96	14.00	2.10
Biennial Idle	9.25	1.16	17.30	2.18	18.50	2.33
Annual Dynamometer	14.00	2.10	14.00	2.10	14.00	2.10
Biennial Dynamometer	18.50	2.33	18.50	2.33	18.50	2.33

- Motor vehicle fuel rules;
- Non-road engine and fuel rules;
- Non-EGU point source controls;
- Nonpoint source controls; and
- Local controls: EGU, non-EGU point source, and nonpoint source.

We tested the sensitivity of the cost analysis to the choice of a default learning rate by re-estimating the total costs of the Amendments using alternative default learning rates of five and 20 percent for the program areas listed above. The five percent default rate represents the low end of the range recommended by the Council, while the 20 percent value represents the central tendency presented in the peer-reviewed literature for several technologies.[8] For the program areas not listed above (i.e., those for which technology- or industry specific learning rates were available), we left cost estimates unchanged.

2.2.5 OTHER UNCERTAINTIES

In addition to the uncertainties outlined above, we identified several other areas of uncertainty related to the costs of the Amendments that we did not address quantitatively. These include the Project Team's projections of economic activity, the impact of CAAA compliance on productivity, the influence of technological innovation on CAAA compliance costs, the impact of input substitution on the costs of complying with the Amendments and the effects of the CAAA on product quality.

- ***Economic Activity Projections***: The cost of the Amendments in 2010 and 2020 will depend in large part on the future size and composition of the U.S. economy. If the AEO 2005 economic growth projections employed by the Project Team underestimate economic activity in 2010 and 2020, the Project Team most likely underestimated the costs of the Amendments. Conversely, the Project Team may have overestimated CAAA compliance costs if AEO 2005 overestimates economic activity in 2010 and 2020. In addition, to the extent that the composition of economic output in 2010 and 2020 deviates from the AEO 2005 projections, the Project Team's cost projections may not reflect the actual costs of the Amendments. *A priori*, it is unclear whether the Project Team would have underestimated or overestimated costs under these circumstances.
- ***Industrial Productivity***: The Project Team's cost estimates represent the direct costs of the Amendments (i.e., the expected expenditures of regulated facilities to comply with the Amendments). Several peer-reviewed studies have suggested, however, that the direct costs of pollution control measures do not adequately represent the total costs of environmental protection, due to the effects of

[8] For an analysis of the learning rates estimated in the empirical literature, see John M. Dutton and Annie Thomas, "Treating Progress Functions as a Managerial Opportunity," *Academy of Management Review*, Vol 9, No. 2, 1984.

pollution abatement on industrial productivity.[9] Although the Project Team's cost estimates do not capture these productivity effects, the literature is not clear on the magnitude and direction of these effects. While some studies have found that pollution control negatively affects productivity, others have found that the productivity impact is positive or ambiguous.[10]

- ***Technological Innovation***: As indicated above, the Project Team's cost estimates reflect the impact of learning (i.e., technological change) as it relates to existing control technologies. The Amendments, however, could serve as in impetus for technological *innovation* in the development of new, low-cost technologies or processes to reduce emissions. Because the Project Team did not attempt to model these technological innovations, the Second Prospective Cost Report may overestimate costs.

- ***Input Substitution***: To minimize the cost of complying with the Amendments, regulated facilities may alter the mix of inputs used in the production of goods and services. With the exception of fuel switching by EGUs, the Project Team did not capture input substitution as a control strategy in the Second Prospective Cost Report. Accordingly, the Project Team may overestimate the costs of the Amendments.

- ***Effects of the CAAA on Product Quality:*** In addition to increasing the cost of producing goods and services, CAAA requirements may also affect product quality. For example, motor vehicle emission control requirements may reduce the performance of automobiles, and changes in paint formulations (to reduce VOC emissions) may adversely affect how well paint adheres to unfinished surfaces. On the other hand, changes in product quality may also have unquantified benefits – while we capture the fuel saving benefits of many motor vehicle engine changes, the benefits of low-VOC paint in improving indoor air quality and human health are not captured in our estimates. As a result, product quality effects may reduce the welfare of households that consume products affected by the CAAA, or they may improve welfare. Households that substitute to other products due to CAAA-related quality changes (e.g., households that

---

[9] Barbera, A.J. and McConnell, V.D. (1986) "Effects of Pollution Control on Industry Productivity: A Factor Demand Approach." The Journal of Industrial Economics. Vol. XXXV, 161-172.

Barbera, A.J. and McConnell, V.D. (1990) "The Impact of Environmental Regulations on Industry Productivity: Direct and Indirect Effects." Journal of Environmental Economics and Management. Vol. 18, 50-65.

Gray, W.B. and Shadbegian, R.J. (1994) "Pollution Abatement Costs, Regulation, and Plant-Level Productivity." Center for Economic Studies.

Morgenstern, R.D., Pizer, W.A., and Shih, J-S. (1998) "The Cost of Environmental Protection." Discussion Paper 98-36. Resources for the Future.

[10] Barbera and McConnell (1986) found a negative impact of pollution control on productivity, while Barbera and McConnell (1990) and Gray and Shadbegian (1994) found an ambiguous impact, and Morgenstern et al. (1998) found a positive impact.

substitute from automobiles to light-duty trucks due to CAAA requirements that affect the performance of automobiles more than light-duty trucks) may also experience welfare losses or gains, as they would have otherwise preferred the product(s) that they would have consumed in the absence of the CAAA but may, in the balance, experience previously unrecognized gains.

2.3 RESULTS

The following four sections present the results obtained using the analytic approach described above for the key cost-related uncertainties.

2.3.1 LOCAL CONTROLS ANALYSIS

The Project Team used a cost cap of $15,000 per ton to estimate the costs of identified local controls and also applied a cost of $15,000 per ton to unidentified controls. To assess the sensitivity of the local controls analysis to changes in these values, we estimated the costs of local controls based on a $10,000 per ton cost cap for identified controls and a $10,000 per ton cost for unidentified controls. As indicated in Exhibits 2-3 and 2-4, this alternative approach yields lower cost estimates for both identified local controls and unidentified measures. The estimated costs of identified controls decline when the $10,000 cap is applied because controls that cost between $10,000 and $15,000 per ton are assumed not to be implemented. In addition, although the application of the $10,000 cost cap increases the emissions reductions to be achieved through unidentified controls (relative to when the $15,000 cost cap is used), reducing the cost of unidentified controls to $10,000 per ton more than offsets the costs associated with these additional emissions reductions.

EXHIBIT 2-3. 2010 LOCAL CONTROLS SENSITIVITY ANALYSIS

PROGRAM AND SECTOR	2010: $15,000/TON CAP AND $15,000/TON FOR UNIDENTIFIED CONTROLS (MILLION 1999$)	2010: $10,000/TON CAP AND $10,000/TON FOR UNIDENTIFIED CONTROLS (MILLION 1999$)
Identified Controls	**$4,564.7**	**$3,380.0**
Ozone NAAQS	$3,729.6	$2,629.4
PM NAAQS	$835.1	$750.6
Unidentified Controls	**$7,581.5**	**$6,959**
Total Cost of Local Controls	**$12,146.2**	**$10,339.0**

Notes:
The cost estimates presented in this exhibit do not reflect the Project Team's cost adjustments for learning curve effects. As indicated in the Second Prospective Cost Report, these adjustments are not applied to unidentified controls and do not have a significant impact on the estimated cost of identified controls.

EXHIBIT 2-4. 2020 LOCAL CONTROLS SENSITIVITY ANALYSIS

PROGRAM AND SECTOR	2020: $15,000/TON CAP AND $15,000/TON FOR UNIDENTIFIED CONTROLS (MILLION 1999$)	2020: $10,000/TON CAP AND $10,000/TON FOR UNIDENTIFIED CONTROLS (MILLION 1999$)
Identified Controls	**$5,757.8**	**$4,387.2**
Ozone NAAQS	$4,130.3	$2,849.2
PM NAAQS	$618.5	$541.6
CAVR	$1,009.0	$996.4
Unidentified Controls	**$11,368.7**	**$9,725**
Total Cost of Local Controls	**$17,126.5**	**$14,112.2**

Notes:
The cost estimates presented in this exhibit do not reflect the Project Team's cost adjustments for learning curve effects. As indicated in the Second Prospective Cost Report, these adjustments are not applied to unidentified controls and do not have a significant impact on the estimated cost of identified controls.

2.3.2 COMPOSITION OF MOTOR VEHICLE SALES AND FLEET FUEL EFFICIENCY

To assess the extent to which cost estimates for the on-road sector would change under the alternative AEO 2008 assumptions, the Project Team estimated the cost of motor vehicle tailpipe and fuel rules for both the 2010 and 2020 target years based on the AEO 2008 data. As indicated in Exhibit 2-5, this would increase the estimated cost of motor vehicle tailpipe standards and reduce the estimated cost of motor vehicle fuel rules, with each effect more pronounced in 2020 than in 2010. In proportional terms, these adjustments would have the most significant effect on the estimated cost of motor vehicle fuel rules in 2020, which would decline by 9 percent relative to the primary cost estimates presented in the Second Prospective Cost Report. Overall, however, the fuel efficiency and sales adjustments would not have a significant effect on the estimated costs of CAAA motor vehicle programs in aggregate. Combined, the sales and fuel efficiency adjustments would reduce the estimated cost of these programs by 0.2 percent in 2010 and by 3.6 percent in 2020.

EXHIBIT 2-5. CAAA-RELATED ON-ROAD SECTOR COSTS BASED ON AEO 2005 AND AEO 2008 ASSUMPTIONS

PROGRAM	TOTAL PROGRAM COSTS (MILLION 1999$)					
	2010			2020		
	PRIMARY ESTIMATE (BASED ON AEO 2005)	ALTERNATIVE ESTIMATE (BASED ON AEO 2008)	PERCENT DIFFERENCE	PRIMARY ESTIMATE (BASED ON AEO 2005)	ALTERNATIVE ESTIMATE (BASED ON AEO 2008)	PERCENT DIFFERENCE
Tailpipe Rules	$8,137	$8,140	0.03%	$8,282	$8,292	0.12%
Fuel Rules	$8,262	$8,216	-0.56%	$9,375	$8,512	-9.20%
Inspection and Maintenance (I/M) Rules	$5,251	$5,251	0.00%	$6,099	$6,099	0.00%
Total On-road Sector Costs	**$21,650**	**$21,606**	**-0.20%**	**$23,757**	**$22,904**	**-3.59%**

2.3.3 VEHICLE INSPECTION FAILURE RATE

To assess the sensitivity of the I&M cost analysis to the assumed failure rate for annual dynamometer-based programs, the Project Team developed alternative cost estimates for CAAA-mandated I&M programs based on the failure rate reported by the NRC. Exhibit 2-6 shows the impact of the alternative failure rates on the estimated cost of CAAA-related I&M programs. As indicated in the exhibit, the estimated cost of these programs declines by more than 40 percent when the alternative failure rates are used in place of those supporting the Second Prospective Cost Report. In addition, using these alternative values reduces total CAAA-related costs for the on-road sector by 11 to 14 percent, depending on the target year. This suggests that the cost estimates for the on-road sector are fairly sensitive to the assumed failure rate for I&M programs, given the range of failure rates obtained from readily available data sources.

2.3.4 DEFAULT LEARNING RATE

The Project Team tested the sensitivity of the cost analysis to the choice of a default learning rate by re-estimating the total costs of the Amendments using alternative default learning rates of five and 20 percent for the program areas listed above. Exhibit 2-7 presents our estimates of total CAAA compliance costs, by sector, using the primary default learning rate of 10 percent and the alternate default learning rates of five and 20 percent. As indicated in the exhibit, the use of alternative default learning rates has only a small effect on the estimated costs of the Amendments. The effect is most pronounced for the 2020 target year. Using a five percent default learning rate in 2020 increases the estimated cost of the Amendments by 3.2 percent, while a 20 percent default learning rate reduces costs by six percent.

EXHIBIT 2-6. CAAA-RELATED ON-ROAD SECTOR COSTS UNDER PRIMARY AND ALTERNATIVE FAILURE RATE ASSUMPTIONS

PROGRAM	TOTAL PROGRAM COSTS (MILLION 1999$)								
	2000			2010			2020		
	PRIMARY ESTIMATE	ALTERNATE ESTIMATE	PERCENT DIFFERENCE	PRIMARY ESTIMATE	ALTERNATE ESTIMATE	PERCENT DIFFERENCE	PRIMARY ESTIMATE	ALTERNATE ESTIMATE	PERCENT DIFFERENCE
Tailpipe and Fuel Rules	$8,219	$8,219	0.00%	$16,399	$16,399	0.00%	$17,657	$17,657	0.00%
Inspection and Maintenance (I/M) Rules	$3,888	$2,217	-42.97%	$5,251	$2,801	-46.66%	$6,099	$3,201	-47.52%
Total On-road Sector Costs	**$12,107**	**$10,436**	**-13.80%**	**$21,650**	**$19,200**	**-11.32%**	**$23,757**	**$20,858**	**-12.20%**

EXHIBIT 2-7. SENSITIVITY OF CAAA COMPLIANCE COST ESTIMATES TO ALTERNATIVE DEFAULT LEARNING RATES

	ANNUAL COST (MILLION 1999$)								
	2000			2010			2020		
	5% LEARNING RATE (ALTERNATE ESTIMATE)	10% LEARNING RATE (PRIMARY ESTIMATE)	20% LEARNING RATE (ALTERNATE ESTIMATE)	5% LEARNING RATE (ALTERNATE ESTIMATE)	10% LEARNING RATE (PRIMARY ESTIMATE)	20% LEARNING RATE (ALTERNATE ESTIMATE)	5% LEARNING RATE (ALTERNATE ESTIMATE)	10% LEARNING RATE (PRIMARY ESTIMATE)	20% LEARNING RATE (ALTERNATE ESTIMATE)
Electric Utilities	$1,154	$1,154	$1,154	$5,583	$5,583	$5,583	$8,836	$8,772	$8,671
On-road Vehicles and Fuels	$12,458	$12,107	$11,462	$22,483	$21,650	$20,119	$24,692	$23,757	$22,039
Non-road Engines and Fuels	$280	$250	$196	$520	$302	-$100	$1,292	$967	$369
Non-EGU Point Sources	$2,561	$2,630	$2,787	$4,407	$4,356	$4,247	$4,448	$4,323	$4,070
Nonpoint Sources	$529	$557	$624	$596	$582	$552	$691	$644	$553
Local Controls	$0	$0	$0	$4,491	$4,415	$4,256	$5,475	$5,194	$4,638
Sub-Total, Excl. Unidentified Measures	**$16,981**	**$16,699**	**$16,223**	**$38,082**	**$36,888**	**$34,657**	**$45,434**	**$43,657**	**$40,340**
ADDITIONAL COSTS FOR UNIDENTIFIED CONTROLS FOR 8-HOUR OZONE COMPLIANCE									
Non-California areas			$0			$7,315			$7,137
California areas			$0			$267			$4,232
TOTAL	**$16,981**	**$16,698**	**$16,223**	**$45,664**	**$44,470**	**$42,239**	**$56,803**	**$55,025**	**$51,709**
Percent Difference from Primary Estimate	1.7%	-	-2.8%	2.7%	-	-5.0%	3.2%	-	-6.0%

CHAPTER 3 | EMISSIONS AND AIR QUALITY MODELING UNCERTAINTY

3.1 INTRODUCTION

This chapter summarizes results from two quantitative sensitivity tests that characterize uncertainty in the emissions and air quality modeling steps of the second prospective analysis.

- **Sectoral emissions sensitivity analyses:** These analyses are designed to explore the relative importance of the emitting sector in marginal benefits estimates, provide a sense of the shape of the marginal benefits curve around the point represented by the *with-Clean Air Act Amendments (CAAA)* scenario emissions inventory, and explore spatial variability in benefits estimates with respect to the emitting sector. The approach adopted is to develop a standardized emissions increment for each of the five major emitting sectors (electric generating units (EGUs); non-EGU point sources; on-road vehicles; nonroad engines; and area sources), and run the alternative scenarios through a reduced form air quality modeling tool and EPA's Environmental Benefits Mapping and Analysis Program (BenMAP) to estimate changes in benefit estimates.
- **EGU sector alternative emissions model:** This analysis estimates model uncertainty for the EGU sector emissions estimation approach, using an alternative emissions estimation approach described in Appendix B of the primary emissions report, *Emission Projections for the Clean Air Act Second Section 812 Prospective Analysis*. The analysis compares the benefits estimates using the Integrated Planning Model (IPM)-based emissions outputs with comparable estimates using Continuous Emissions Monitor (CEM) data and an alternative approach to estimating counter-factual scenario emissions.

Note that, in addition to these quantitative analyses, IEc subcontractor Sonoma Technology, Inc (STI) conducted a three part literature review relating to the uncertainties in Integrated Air Quality Modeling Systems (IAQMSs). The first part of this literature review looks at the source of uncertainty and methods for quantifying these uncertainties. The second part looks at the literature relating to the evaluation and overall reliability of IAQMSs. The third part discusses the uncertainties specifically relating to the IAQM used in the Second Prospective Analysis (i.e., the Community Multiscale Air Quality (CMAQ) modeling system). This literature review can be found in its entirety in Appendix B. The literature review is part of our overall suite of uncertainty analyses that inform characterization of the costs and benefits of CAAA programs.

3.2 DESCRIPTION OF ANALYTICAL TOOLS

The main tools used to develop these analyses are EPA's Particulate Matter Response Surface Model (PM RSM), a reduced form air quality estimation tool, and BenMAP. PM RSM estimates air quality outcomes from emissions inputs, and BenMAP estimates health effects and economic benefits outcomes from air quality inputs. The two tools are linked in our analyses to estimate the impact of uncertainties in emissions estimates.

3.2.1 RESPONSE SURFACE MODEL

The description of this tool is largely taken from EPA's *Technical Support Document for the Proposed PM NAAQS Rule: Response Surface Modeling.*[11] Response surface modeling provides a means to address the limitations of using complex air quality models for policy analysis. Air quality models such as CMAQ typically require complicated emission inputs and processing, and the resources needed to conduct model runs can be substantial. These requirements make such sophisticated models less well-suited for uncertainty analysis, where the analyst may want to conduct multiple model runs while varying key inputs or assumptions. Response surface modeling builds reduced form modeling tools by using advanced statistical techniques to characterize, in a more parsimonious manner, the relationship between the outputs of a complex model and its input parameters. The result is a more flexible, less resource intensive model of the original model (a "meta-model) that can be used as a reasonable proxy for conducting uncertainty analysis within the calibration range of the meta-model. This analysis makes use of a PM RSM developed by EPA to estimate results from the CMAQ Modeling System.

CMAQ is a three-dimensional regional grid-based air quality model designed to simulate particulate matter and ozone concentrations and deposition over large spatial scales (e.g., over the contiguous U.S.) over an extended period of time (e.g., up to a year). The CMAQ model includes state-of-the-science capabilities for conducting urban to regional scale simulations of multiple air quality issues, including tropospheric ozone, fine particles, air toxics, acid deposition, and visibility degradation. The PM RSM used in this analysis is based on air quality modeling using CMAQ version 4.4.

Response surface models are typically developed using a limited number of runs of the complex model at a set of statistically selected points in the design space. A total of 180 CMAQ model runs, meant to cover a change in baseline precursor emissions of zero to 120 percent, were conducted for development of the PM RSM. The response-surface method uses statistical techniques to relate a response variable from these runs (in this case, $PM_{2.5}$ concentration output from CMAQ) to a set of factors (in this case, $PM_{2.5}$ precursor pollutants from particular sources and locations). To develop a response surface approximation for CMAQ, EPA used an interpolation approach, implemented through the MIXED procedure in SAS software. The PM RSM models changes in $PM_{2.5}$

[11] U.S. Environmental Protection Agency, Office of Air Quality Planning and Standards. Technical Support Document for the Proposed PM NAAQS Rule: Response Surface Modeling. February 2006.

concentration at the grid cell level as a function of the weighted average of the modeled responses from the 180 CMAQ runs. Weights were assigned based on the distance between the factor levels defining the policy to be predicted and the factors defining the CMAQ experimental run.

The main purpose of the PM RSM is to demonstrate the impact on ambient $PM_{2.5}$ concentrations of reductions in $PM_{2.5}$ precursor emissions from different sources. EPA selected the precursor emission type and source combinations used as input factors into the model to provide maximum information for use in comparing relative effectiveness of different emission control strategies. Emission input factors are expressed as a percent of a 2015 baseline scenario that includes the Clean Air Interstate Rule (CAIR), Clean Air Non-Road Diesel Rule, Heavy Duty Diesel Rule, Tier 2, and the NO_x SIP Call. EPA selected the following 12 emission input factors for use in the PM RSM; users of the PM RSM can adjust these at a local or regional scale:

1) NO_x EGU – Nitrogen oxide (NO_x) emissions from EGU point sources forecast using the Integrated Planning Model (IPM);
2) NO_x Non-EGU and Area – NO_x emissions from Non-EGU point sources forecast using IPM and from area sources, including agricultural sources;
3) NO_x Mobile – NO_x emissions from non-road and on-road mobile sources;
4) SO_x EGU – Sulfur oxide (SO_x) emissions from EGU point sources forecast using IPM;
5) SO_x Non-EGU – SO_x emissions from Non-EGU point sources forecast using IPM;
6) SO_x Area – SO_x emissions from area sources, including agricultural sources, and from non-road and on-road mobile sources[12];
7) NH_3 Area – Ammonia (NH_3) emissions from area source, including agricultural sources;
8) NH_3 Mobile – Ammonia emissions from non-road and on-road mobile sources;
9) POC/PEC Point – Particulate organic carbon (POC) and Particulate elemental carbon (PEC) emissions from EGU and Non-EGU point sources forecast using IPM;
10) POC/PEC Mobile – POC and PEC emissions from non-road and on-road mobile sources;
11) POC/PEC Area – POC and PEC emissions from area sources, including agricultural sources; and

[12] When it was developed by EPA this factor included only area-source emissions and mobile-source SO_x emissions were not included as an emission input factor in the model. Feeling that these emissions were significant, the Project Team elected to include them as part of this factor rather than leave them out of the model.

12) VOC All – Volatile organic carbon (VOC) emissions from EGU point sources, non-EGU point sources, area sources including agricultural sources, non-road and on-road mobile sources.

The PM RSM includes an independent response surface for particular urban areas, as well as a generalized response surface for all other locations. A rigorous area-of-influence analysis was conducted for selection of PM RSM urban locations to discern the degree of overlap between different urban areas in terms of air quality impacts, and to tease out local versus regional impacts. The analysis concluded that ambient $PM_{2.5}$ in each of the nine selected urban areas is largely independent of the precursor emissions in all other included urban areas. The nine selected urban areas are New York/Philadelphia (combined), Chicago, Atlanta, Dallas, San Joaquin, Salt Lake City, Phoenix, Seattle, and Denver.

Potential limitations of the PM RSM are that:

- The PM RSM is designed to estimate $PM_{2.5}$ concentrations resulting from changes in precursor emissions between zero and 120 percent of 2015 baseline emission levels. The model has not been validated for accuracy outside of these bounds. The overall second prospective analysis does in many cases look at changes in precursor emission greater than 120 percent. The Project Team limits changes to 500 percent of the baseline to avoid straying too far outside the calibrated bounds of the PM RSM. The 500 percent limitation was developed based on Project Team analysis of results and inspection of the marginal response curves for PM outcomes relative to each of the twelve emissions inputs.
- The PM RSM is only capable of dealing with geographical differentiation of emission policies within the nine local areas. In general, our analysis is focused on National-level emissions policy, but the emissions changes are not uniform at the county-level resolution of our emissions inventories. Our sectoral emissions sensitivity analyses therefore focus on relative comparisons of uniform emissions changes, rather than absolute differences in PM RSM outcomes.

One result of these limitations is that core scenario air quality and benefit results are very different for PM RSM and CMAQ. For the same 2010 emissions scenarios, PM RSM results yield an estimated 31,000 avoided premature mortalities, while CMAQ results yield 102,000, a difference of more than three-fold.[13] This large discrepancy in results is the main reason that our analyses focus mainly on relative comparisons of PM RSM runs, rather than hypotheses that depend on absolute air quality or benefits outcomes.

[13] These avoided premature mortality estimates are based on the PM/mortality concentration-response (C-R) function from Pope et al. (2002). The integrated report and the remainder of this report rely on an alternative C-R function (i.e., a Weibull distribution based on epidemiological evidence and expert elicitation results) that was recommended by the Council following the completion of this emissions uncertainty analysis. Despite this discrepancy, we believe the relative results of this analysis compared across sectors provide useful insights.

3.2.2 BENMAP

EPA's BenMAP benefits modeling tool generates national-level estimates of avoided health effects due to changes in $PM_{2.5}$ between a baseline scenario (i.e., air pollution levels in the absence of control regulations) and a control scenario (i.e., air pollution levels after a control regulation is put into place). BenMAP applies health impact functions relating the change in $PM_{2.5}$ concentration to the change in the incidence of a health endpoint, taking into consideration the baseline incidence rate of the health endpoint and the exposed population in the target year of the analysis. BenMAP then applies valuation functions to estimate the economic benefits of the changes in the incidence of the health effect.

The $PM_{2.5}$ concentration output from CMAQ and PM RSM was used as input for BenMAP to generate health impacts and associated economic values for each emissions and air quality modeling scenario. Exhibit 3-1 presents the 27 BenMAP runs undertaken for this analysis grouped by scenario type. The PM RSM and/or CMAQ output for each scenario was converted into air quality grids that could be uploaded into BenMAP. Exhibit 3-1 also shows which scenario was used for the baseline and control scenarios in BenMAP. The Project Team then ran BenMAP using incidence and pooling/aggregation configuration files patterned after those used in the PM National Ambient Air Quality Standards (NAAQS) Regulatory Impact Analysis (RIA).[14] However, we did not incorporate a population-level threshold in the $PM_{2.5}$ mortality impact functions from the Pope et al. (2002) and Laden et al. (2006) studies, as was done in that analysis.[15,16]

3.3 METHODS FOR QUANTITATIVE EMISSIONS UNCERTAINTY ANALYSES

The Project Team quantitatively analyzed uncertainty related to emissions by running various emissions scenarios through PM RSM and BenMAP and analyzing the results. We grouped these into three categories:

- Core scenarios – *with*- and *without-CAAA* scenarios for the three target years (2000, 2010, and 2020). These were essentially "control runs" to examine how PM RSM performed relative to the CMAQ.
- Sector-specific emission scenarios – these scenarios were developed in an attempt to estimate changes in $PM_{2.5}$ concentration and corresponding health benefits associated with small incremental changes in sector-specific emissions.

[14] U.S. Environmental Protection Agency. (2006). *Final Regulatory Impact Analysis: $PM_{2.5}$ NAAQS. Office of Air and Radiation*, Research Triangle Park, NC.

[15] Pope, C. A., R. T. Burnett, et al. (2002). Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. *Journal of the American Medical Association* 287(9): 1132-1141.

[16] Laden, F., J. Schwartz, et al. (2006). Reduction in Fine Particulate Air Pollution and Mortality: Extended Follow-up of the Harvard Six Cities Study. *American Journal of Respiratory and Critical Care Medicine* 173: 667-672.

- Alternative EGU emission scenarios – these scenarios assess model uncertainty by evaluating benefits results for an alternative method of estimating EGU emissions.

We describe each of these scenario categories in more detail below.

EXHIBIT 3-1. BENMAP RUNS FOR THE 812 UNCERTAINTY ANALYSIS

BENMAP SCENARIO	AIR QUALITY MODEL USED	BASELINE SCENARIO	CONTROL SCENARIO
CORE SCENARIOS			
2000	CMAQ and PM RSM	2000 without CAAA	2000 with CAAA
2010	CMAQ and PM RSM	2010 without CAAA	2010 with CAAA
2020	CMAQ and PM RSM	2020 without CAAA	2020 with CAAA
ALTERNATIVE EGU SCENARIOS			
2000 Alt EGU	PM RSM	2000 Ellerman Counterfactual	2000 CEM data
SECTOR-SPECIFIC EMISSION SCENARIOS			
2010 EGU hi	PM RSM	2010 with CAAA	2010 with CAAA, EGU hi
2010 Non-EGU hi	PM RSM	2010 with CAAA	2010 with CAAA, Non-EGU hi
2010 Area hi	PM RSM	2010 with CAAA	2010 with CAAA, Area hi
2010 On-Road hi	PM RSM	2010 with CAAA	2010 with CAAA, On-Road hi
2010 Non-Road hi	PM RSM	2010 with CAAA	2010 with CAAA, Non-Road hi
2010 EGU lo	PM RSM	2010 with CAAA	2010 with CAAA, EGU lo
2010 Non-EGU lo	PM RSM	2010 with CAAA	2010 with CAAA, Non-EGU lo
2010 Area lo	PM RSM	2010 with CAAA	2010 with CAAA, Area lo
2010 On-Road lo	PM RSM	2010 with CAAA	2010 with CAAA, On-Road lo
2010 Non-Road lo	PM RSM	2010 with CAAA	2010 with CAAA, Non-Road lo
2020 EGU hi	PM RSM	2020 with CAAA	2020 with CAAA, EGU hi
2020 Non-EGU hi	PM RSM	2020 with CAAA	2020 with CAAA, Non-EGU hi
2020 Area hi	PM RSM	2020 with CAAA	2020 with CAAA, Area hi
2020 On-Road hi	PM RSM	2020 with CAAA	2020 with CAAA, On-Road hi
2020 Non-Road hi	PM RSM	2020 with CAAA	2020 with CAAA, Non-Road hi
2020 EGU lo	PM RSM	2020 with CAAA	2020 with CAAA, EGU lo
2020 Non-EGU lo	PM RSM	2020 with CAAA	2020 with CAAA, Non-EGU lo
2020 Area lo	PM RSM	2020 with CAAA	2020 with CAAA, Area lo
2020 On-Road lo	PM RSM	2020 with CAAA	2020 with CAAA, On-Road lo
2020 Non-Road lo	PM RSM	2020 with CAAA	2020 with CAAA, Non-Road lo

3.3.1 CORE SCENARIOS

The Project Team generated six "core scenarios" representing the ambient $PM_{2.5}$ concentrations in three target years (2000, 2010, and 2020) under each of two scenarios (a "*with-CAAA*" scenario and a "*without-CAAA*" scenario). The *with-CAAA* scenarios rely on emissions input data that reflects expected or likely future measures implemented since the 1990 CAAA. The counterfactual *without-CAAA* scenarios utilize emission input data that is derived by freezing the scope and stringency of emissions controls at their 1990 levels, while allowing for growth in population and economic activity. The core scenarios were also run through CMAQ and provide a base from which to compare the other scenarios used to gauge emission uncertainty. The CMAQ results provide the basis for the primary benefits estimates generated for the study. Because the PM RSM is much less resource-intensive to run, we use the PM RSM runs to evaluate a much broader range of alternative emissions outcomes.[17]

3.3.2 SECTOR-SPECIFIC EMISSION SCENARIOS

The sector scenarios attempt to estimate changes in $PM_{2.5}$ concentration and corresponding health benefits associated with small incremental changes in sector-specific emissions both above and below the emissions estimates used in the 2010 and 2020 core *with-CAAA* scenarios. It was difficult to select a fixed amount to increase or decrease emissions within each sector because emission levels and pollutant mix vary greatly over the five emitting sectors. For example, 2010 SO_x emissions from non-road sources equal approximately 16,900 tons, while SO_x emissions from EGU sources equal approximately 6,370,000 tons. Because of this variation, incremental changes were determined as a percentage of sector-specific emissions.

The Project Team determined that increasing/decreasing sector-specific emissions by ten percent results in changes large enough to impact $PM_{2.5}$ concentrations for all sectors, yet small enough to be considered incremental. The Project Team also determined that changes in precursor emissions should be limited to five times the 2015 baseline emission levels (i.e., limited factors to a value of five).[18] As is described above, the PM RSM is designed to cover changes in the baseline precursor emissions between zero and 120 percent. EPA has not validated the model for changes outside these bounds and the Project Team has found that changes above 500 percent may lead to unexpected results.

After determining how to calculate the incremental change, it was necessary to determine how to distribute the change over the local (Atlanta, Chicago, NYC/Philadelphia, Dallas, Denver, Salt Lake City, Phoenix, San Joaquin, and Seattle) and regional (East and West) PM RSM domains. The most straightforward manner in which to distribute the incremental change is based on a local area or region's share of the total sector-specific emissions. For example, if the Atlanta area has 25 percent of the SOx EGU emissions in 2010, then 25 percent of the incremental change in SOx EGU emissions was applied to the Atlanta area.

[17] Note that the PM RSM was originally calibrated to CMAQ, but for a more limited range of emissions inputs than we ultimately need for the core comparison of the *with-CAAA* and *without-CAAA* scenario. As a result, it remains limited in its ability to assess the emissions changes implied by the *without-CAAA* core scenarios, because the absolute emissions in those scenarios are outside the range of calibration for the tool. As a result, in this chapter we rely on PM RSM only for those scenarios that most closely match its range of calibration.

[18] The Project Team initially analyzed scenarios that increased/decreased sector-specific emissions by 25 percent and limited emission input factor levels to ten times the 2015 baseline level (i.e., limited factors to a value of ten). After conducting this analysis, we determined that a smaller percentage change could be used and that, in some cases, factors above five lead to unexpected results.

Applying the ten percent incremental change both above and below the emissions estimates used in the 2010 and 2020 core *with-CAAA* scenarios resulted in 20 sector scenario PM RSM runs (five sectors per scenario per year). Exhibit 3-2 provides the resulting emissions changes for pollutant/sector combinations used to develop PM RSM inputs.

EXHIBIT 3-2 10 PERCENT CHANGE IN PRECURSOR EMISSIONS FROM *WITH-CAAA* SCENARIO EMISSIONS LEVELS (TONS)

SCENARIO	VOC	NO_X	SO_2	NH_3	POC AND PEC	TOTAL
2010						
EGU	4,266	243,722	636,546	82	3,096	890,809
NonEGU	143,550	224,660	217,706	17,392	4,078	611,462
Area	887,228	368,831	187,765	371,317	86,673	1,988,486
OnRoad	261,401	434,906	2,995	33,442	8,236	749,216
NonRoad	187,472	164,341	1,693	204	14,132	381,974
2020						
EGU	4,699	198,646	427,013	56	4,313	639,040
NonEGU	164,756	250,903	238,732	20,163	4,661	683,877
Area	971,557	372,498	194,175	398,677	88,595	2,114,096
OnRoad	167,062	191,584	3,646	39,532	5,732	413,288
NonRoad	148,964	99,892	275	240	9,164	267,698

3.3.3 ALTERNATIVE EGU EMISSION SCENARIOS

In response to differences between the spatial distribution of emissions as modeled by IPM and the actual spatial distribution from CEM data, and differences in modeled versus actual fuel and allowance prices for the historical (*with-CAAA*) case, the Project Team has developed an alternative approach for modeling the effect of the CAAA on the EGU sector in the year 2000. The Project Team generated EGU point source emissions data for the *with-CAAA* scenario using continuous CEM data available on EPA's Clean Air Markets website.[19] We estimated EGU data for the *without-CAAA* scenario using an alternative counterfactual approach based on work done by Dr. A. Denny Ellerman of Massachusetts Institute of Technology.[20] The data for all other emission sources (non-EGU, on-road, non-road, and area) were held constant at levels consistent with the *with-CAAA* 2000 core scenario level.

[19] U.S. Environmental Protection Agency. Clean Air Markets - Data and Maps <http://camddataandmaps.epa.gov/gdm/> Accessed March 2009.

[20] Dr. A. Denny Ellerman's approach relies on multiplying a "baseline" pre-Title IV emissions rate by 2001 CEM heat input observations for each electric generating unit.

3.4 RESULTS

3.4.1 CORE SCENARIOS

Exhibit 3-3 depicts the PM RSM results for each of the core scenarios. The core scenario PM RSM results are presented here mainly for context, because the results of the *with-CAAA* scenario are used as a baseline in evaluating the marginal effect of changes in emissions from major emitting sectors.

The PM RSM results match the general trends in the emissions inputs, as follows:

1. As expected, for each year in the analysis the *without-CAAA* scenario has higher $PM_{2.5}$ concentrations than the *with-CAAA* scenario.
2. Overall and on average $PM_{2.5}$ concentrations gradually decrease over time for the *with-CAAA* scenarios and the *without-CAAA* scenarios.
3. Over time, the gap between $PM_{2.5}$ concentrations in the *with-CAAA* and *without-CAAA* scenario widens.

The PM RSM results also provide a reasonable approximation of the results based on CMAQ, a much more complex and highly resolved model. There are nonetheless some important differences in the PM RSM and CMAQ results, as illustrated in Exhibit 3-4 for the target year 2010.[21] First, the PM RSM *with-CAAA* results indicate higher PM concentrations than CMAQ. This suggests that PM RSM may be somewhat less responsive to input changes than CMAQ, at least for our scenario. Second, PM RSM shows lower PM concentrations in the East, and higher concentrations in the West, particularly California, than CMAQ. This may be attributable to PM RSM's more limited ability to reflect complex interactive effects among pollutants, which could be important in the East where SO_x is affected by the ammonium levels, and in the West where precursors contribute to high levels of both PM and ozone (the PM RSM does not simulate ozone formation). Third, although differences between the two scenarios are not presented in Exhibit 3-4, the impact of the first two factors is that CMAQ estimates a much greater impact of the CAAA on air quality differences.

These factors suggestion caution is warranted in drawing conclusions based on the PM RSM estimates. We believe that comparisons of PM RSM runs provide insights into the marginal effect of emissions, and relative effect among emitting sectors, but also that PM RSM in general is likely to be less sensitive to emissions changes. As a result, the results we present in this chapter likely understate the absolute value of emissions differences among scenarios.

[21] The CMAQ results presented in Exhibit 3-4 reflect the impact of the MATS calibration procedure.

EXHIBIT 3-3 CORE SCENARIO PM RSM RESULTS FOR 2000, 2010, AND 2020

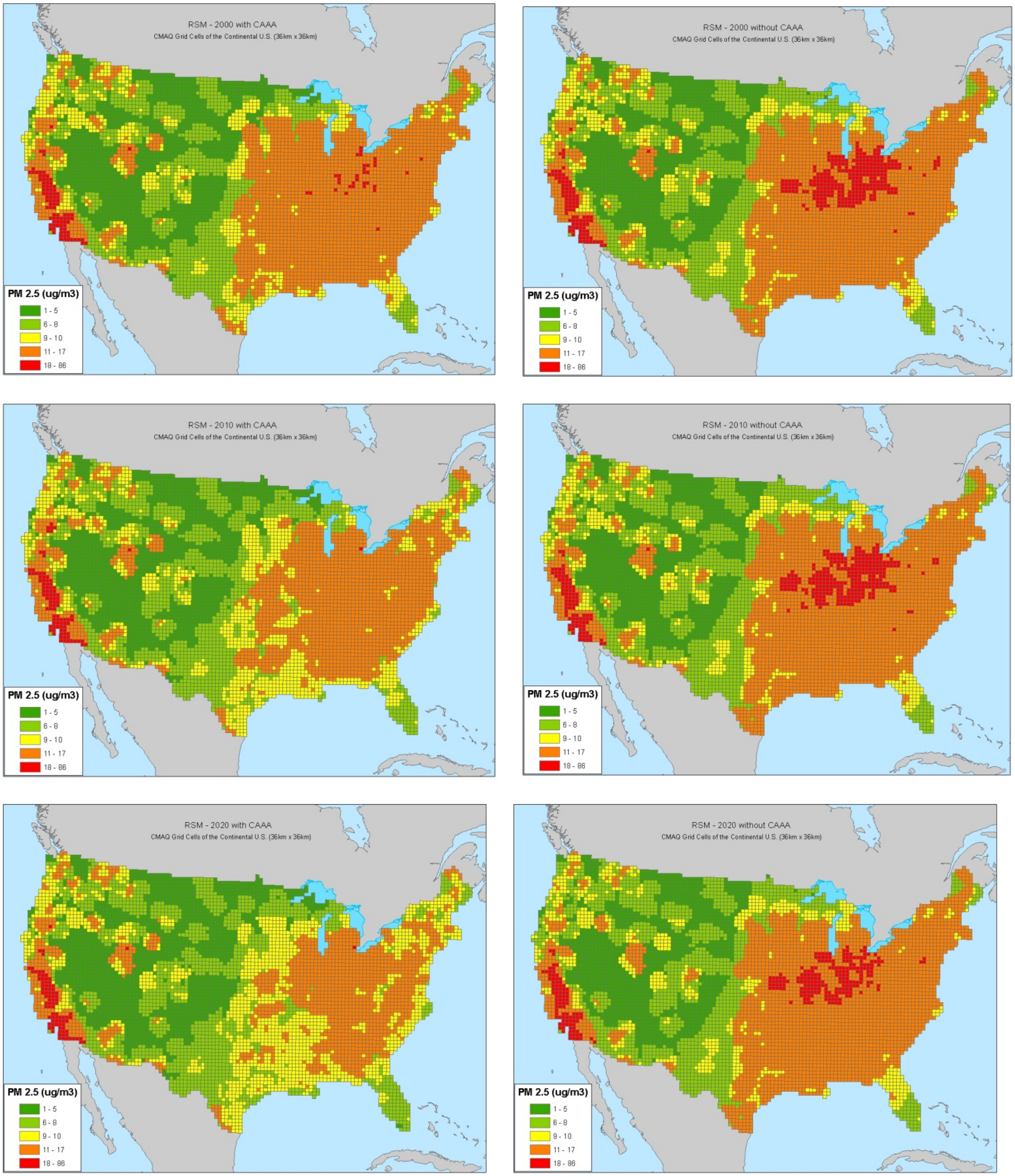
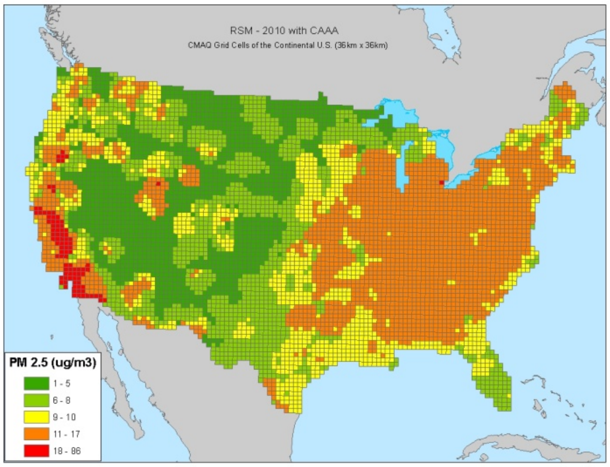
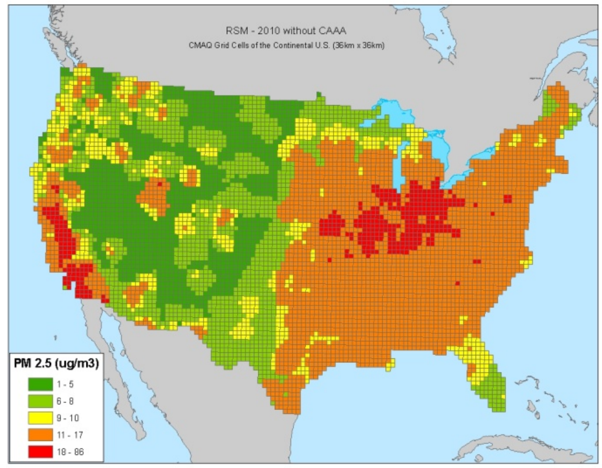


EXHIBIT 3-4 2010 PM RSM AND CMAQ RESULTS[22]

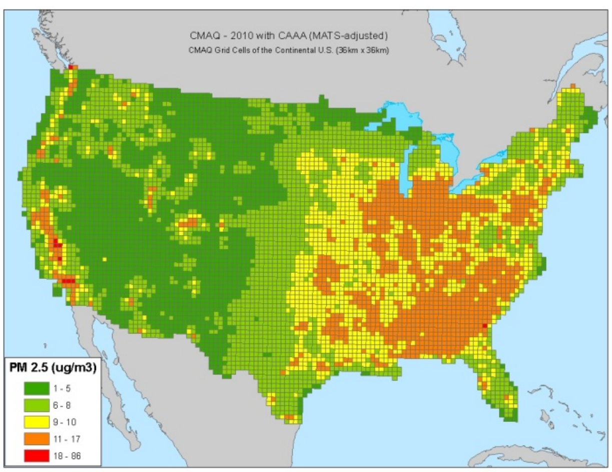
2010 with CAAA **2010 without CAAA**

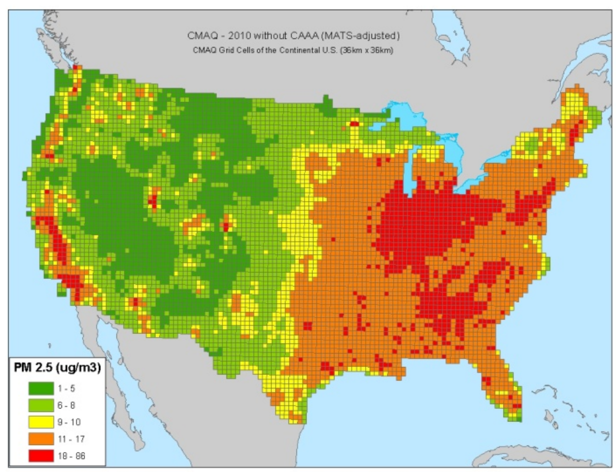
PM RSM





CMAQ





[22] Note that these results do not take into account the PM adjustment factors that were applied to the $PM_{2.5}$ concentrations in the integrated report and the results reflected in the other chapters of this report. However, the purpose of these figures is to make relative comparisons between CMAQ and RSM rather than to represent absolute $PM_{2.5}$ results.

EXHIBIT 3-5 PM BENEFITS OF CAAA DERIVED USING RSM OUTPUT

ENDPOINT GROUP	INCIDENCE			VALUATION (MILLION 2006$)		
	PERCENTILE 5	MEAN	PERCENTILE 95	PERCENTILE 5	MEAN	PERCENTILE 95
2000						
Mortality – Pope et al., 2002	4,540	12,300	20,100	$32,700	$83,100	$141,000
			Total	$34,200	$89,200	$158,000
2010						
Mortality – Pope et al., 2002	11,600	31,300	51,000	$89,100	$225,000	$380,000
			Total	$93,100	$241,000	$426,000
2020						
Mortality – Pope et al., 2002	12,500	38,900	65,100	$109,000	$303,000	$525,000
			Total	$114,000	$324,000	$587,000

Notes:

1. Results are rounded to three significant figures.
2. The valuation totals represent low, central, and high estimates. The low and high estimates were calculated by taking the sum of the 5th and 95th percentiles of the valuation estimates for each health endpoint. An alternative would be to calculate actual percentiles for the aggregated valuation estimates, but this is not what is presented here.
3. 20-year distributed lag and five percent discount rate applied to mortality results.
4. These results are based on the PM-mortality C-R function from Pope et al. (2002) rather than the primary estimate (Weibull distribution) used in the integrated and benefits reports as well as in the remainder of this report. In addition, these results have not been adjusted using the PM adjustment factors to correct analytical issues affecting the $PM_{2.5}$ concentration values. However, these results are intended to provide a relative comparison of RSM with CMAQ, rather than absolute benefits results.

We generated benefits results for the PM RSM core scenarios as well, using PM RSM air quality outputs as BenMAP inputs.[23] The summary results are illustrated in Exhibit 3-5. As expected, mortality benefits dominate the health benefit results. In addition, health benefits of the CAAA increase over time. This result is consistent with the increasing gap in $PM_{2.5}$ concentrations observed in the PM RSM results. Also consistent with the PM RSM results is the fact that there is a large increase in the number of avoided deaths (as well as other health benefits) between 2000 and 2010, but only a moderate increase between 2010 and 2020. Overall and on average the difference between $PM_{2.5}$ concentrations in the *with*- and *without-CAAA* scenarios also increases steeply between 2000 and 2010, but only moderately between 2010 and 2020. Comparing these PM RSM results to CMAQ results in Chapter 2 of the Second Prospective Benefits Report, however, it is clear that PM RSM estimates much smaller benefits of the CAAA than CMAQ for the same emissions scenarios. This result provides further reason for interpreting the absolute PM RSM results with caution.

3.4.2 SECTOR-SPECIFIC EMISSION SCENARIOS

Exhibit 3-6 depicts the difference in $PM_{2.5}$ concentrations between each of the 10 sector scenarios for 2020 and the corresponding core *with-CAAA* scenario. Difference maps are used to depict these results because the differences in actual $PM_{2.5}$ concentrations over the scenarios are not noticeable on a map. In this exhibit, shades of green indicate that $PM_{2.5}$ concentrations are lower in the sector scenario than in the corresponding core scenario and shades of yellow, orange, and red indicate that $PM_{2.5}$ concentrations are higher in the sector scenario than in the corresponding core scenario.

These maps indicate that increasing/decreasing EGU and Area emissions seem to have the greatest impact on $PM_{2.5}$ concentrations. These results are not surprising because the overall level of Area- and EGU-specific emissions are higher than the other sector-specific emissions (Non-EGU, On-Road, and Non-Road) and thus a 10 percent change will necessarily lead to greater impacts.

Exhibit 3-7 provides the mean incidence and valuation results for sector-specific emission increases and decreases in 2010 and 2020. The BenMAP results are in line with the PM RSM results in that increases in Area- and EGU-specific emissions lead to the greatest damages, while conversely, decreases in these sector-specific emissions lead to the greatest benefits, consistent with the overall greater level of Area- and EGU-specific emissions. Damages and benefits are of approximately the same scale of magnitude, but differ across years and sector in a curious pattern. In 2010, the EGU and non-EGU sectors show very close agreement between damages and benefits, but in the non-road, onroad, and area source sectors, decreases in emissions yield larger benefits than the

[23] The benefits results are based on the PM-mortality C-R function from Pope et al. (2002) rather than the primary estimate (Weibull distribution) used in the integrated and benefits reports as well as in the remainder of this report. In addition, these results have not been adjusted using the PM adjustment factors to correct analytical issues affecting the $PM_{2.5}$ concentration values. However, these results are intended to provide a relative comparison of RSM with CMAQ, rather than absolute benefits results.

comparable increase in emissions yields damages. This might suggest that, at the margin in 2010, there is an increasing marginal benefit curve for additional reductions for these three sectors. By 2020, all the sectors except for area sources emissions show close agreement between damages from a 10 percent increase and benefits from a 10 percent decrease, which may suggest that the marginal benefits curve for most sectors is flat, but for area sources remains upward sloping.

EXHIBIT 3-6 2020 SECTOR-SPECIFIC EMISSION SCENARIO DIFFERENCE MAPS

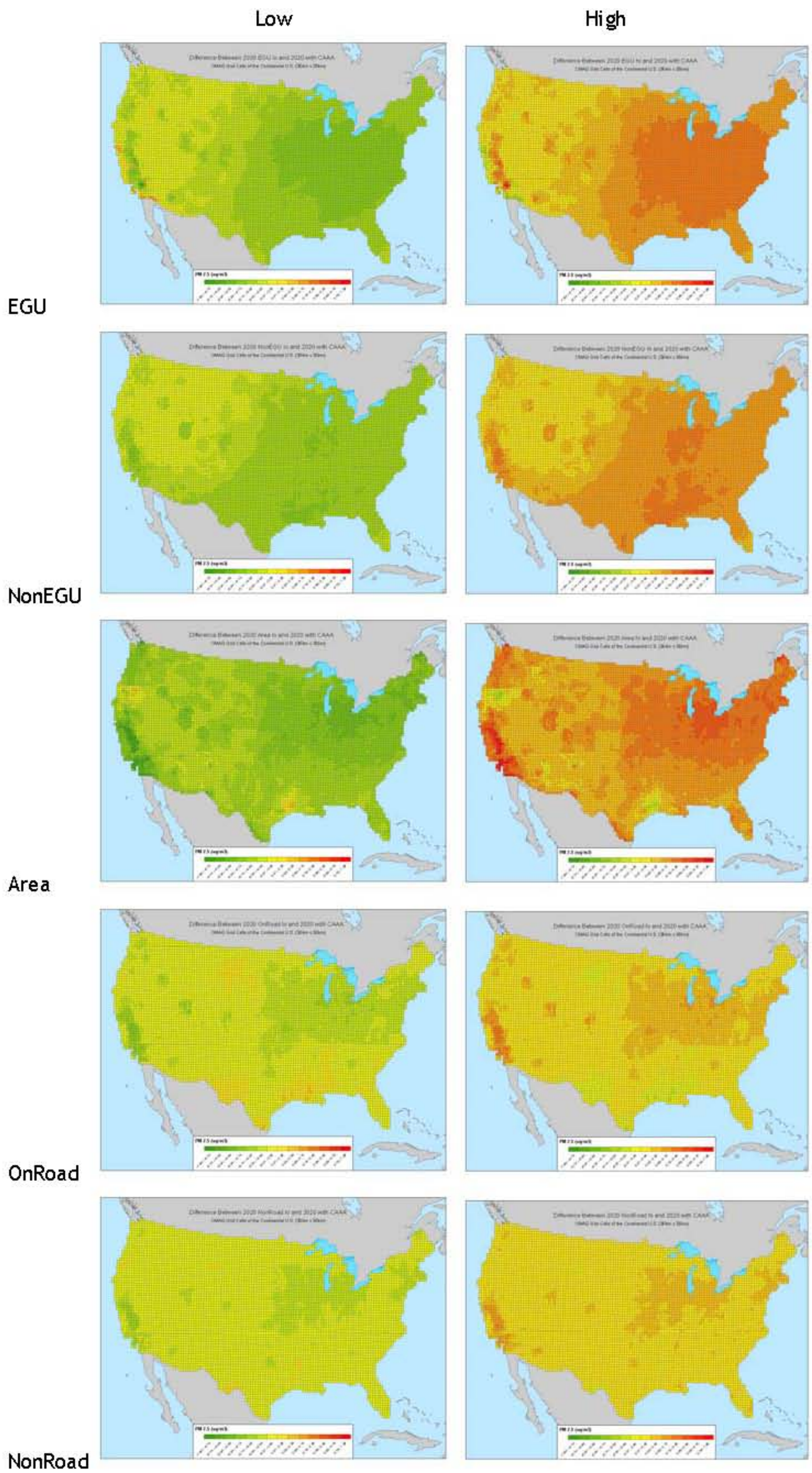


EXHIBIT 3-7 MEAN DAMAGES/BENEFITS ARISING FROM A 10% INCREASE/DECREASE IN SECTOR-SPECIFIC EMISSIONS

ENDPOINT GROUP	EGU		NON-ROAD		ON-ROAD		NON-EGU		AREA	
	INCIDENCE	VALUATION (MIL 2006$)	INCIDENCE	VALUATION (MIL 2006$)	INCIDENCE	VALUATION (MIL 2006$)	INCIDENCE	VALUATION (MIL 2006$)	INCIDENCE	VALUATION (MIL 2006$)
2010 – INCREASE										
Mortality – Pope et al., 2002	-2,860	-$19,400	-472	-$3,150	-648	-$4,380	-1,110	-$7,490	-4,050	-$27,200
Total	--	-$20,900	--	-$3,400	--	-$4,740	--	-$8,040	--	-$29,400
2010 – DECREASE										
Mortality – Pope et al., 2002	2,800	$20,200	450	$3,230	688	$4,970	1,170	$8,500	4,300	$31,100
Total	--	$21,600	--	$3,470	--	$5,350	--	$9,080	--	$33,400
2020 – INCREASE										
Mortality – Pope et al., 2002	-2,420	-$18,800	-388	-$3,000	-554	-$4,320	-1,570	-$12,200	-4,610	-$35,900
Total	--	-$20,100	--	-$3,210	--	-$4,640	--	-$13,000	--	-$38,500
2020 – DECREASE										
Mortality – Pope et al., 2002	2,310	$18,100	343	$2,650	557	$4,350	1,480	$11,600	5,050	$39,300
Total	--	$19,300	--	$2,840	--	$4,670	--	$12,300	--	$41,100

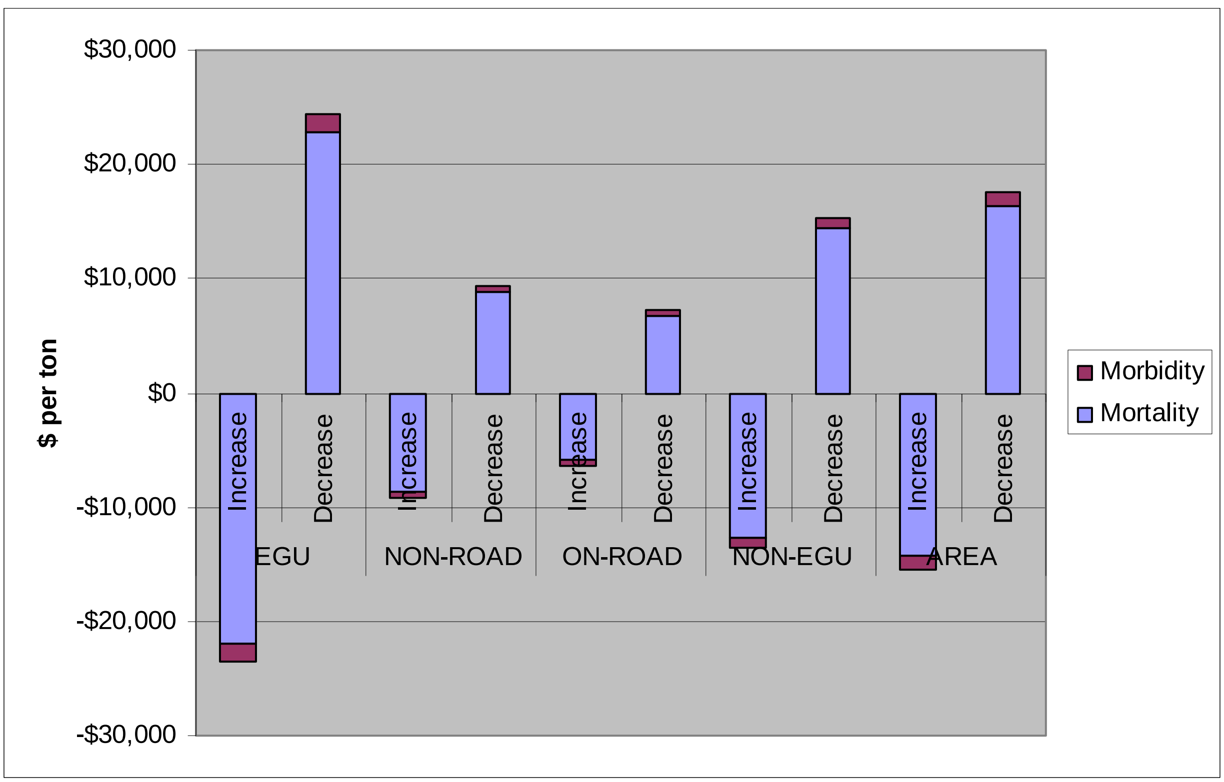
Notes:

1. Results are rounded to three significant figures.
2. The valuation totals represent low, central, and high estimates. The low and high estimates were calculated by taking the sum of the 5th and 95th percentiles of the valuation estimates for each health endpoint. An alternative would be to calculate actual percentiles for the aggregated valuation estimates, but this is not what is presented here.
3. 20-year distributed lag and five percent discount rate applied to mortality results.
4. Negative values reflect damages relative to the baseline and are the result of higher $PM_{2.5}$ ambient air quality concentrations in the control scenario than in the baseline. Control scenarios with lower concentrations than the baseline yield positive benefits.
5. These results are based on the PM-mortality C-R function from Pope et al. (2002) rather than the primary estimate (Weibull distribution) used in the full integrated and benefits report as well as in the remainder of this report. In addition, these results have not been adjusted using the PM adjustment factors to correct analytical issues affecting the $PM_{2.5}$ concentration values. However, these results are intended to provide a relative comparison of sector-specific emissions using RSM, rather than absolute benefits results.

In order to better compare the relative damages/benefits associated with changes in sector-specific emissions the Project Team calculated dollar per ton values. The methodology used to calculate dollar per ton values is similar to that used in the Ozone NAAQS RIA to calculate benefit per-ton metrics that were used as the basis for estimating the $PM_{2.5}$ co-benefits.[24] After benefits/damaged were calculated using BenMAP, the Project Team divided these monetized values by the total precursor emission reductions/increases for each scenario.

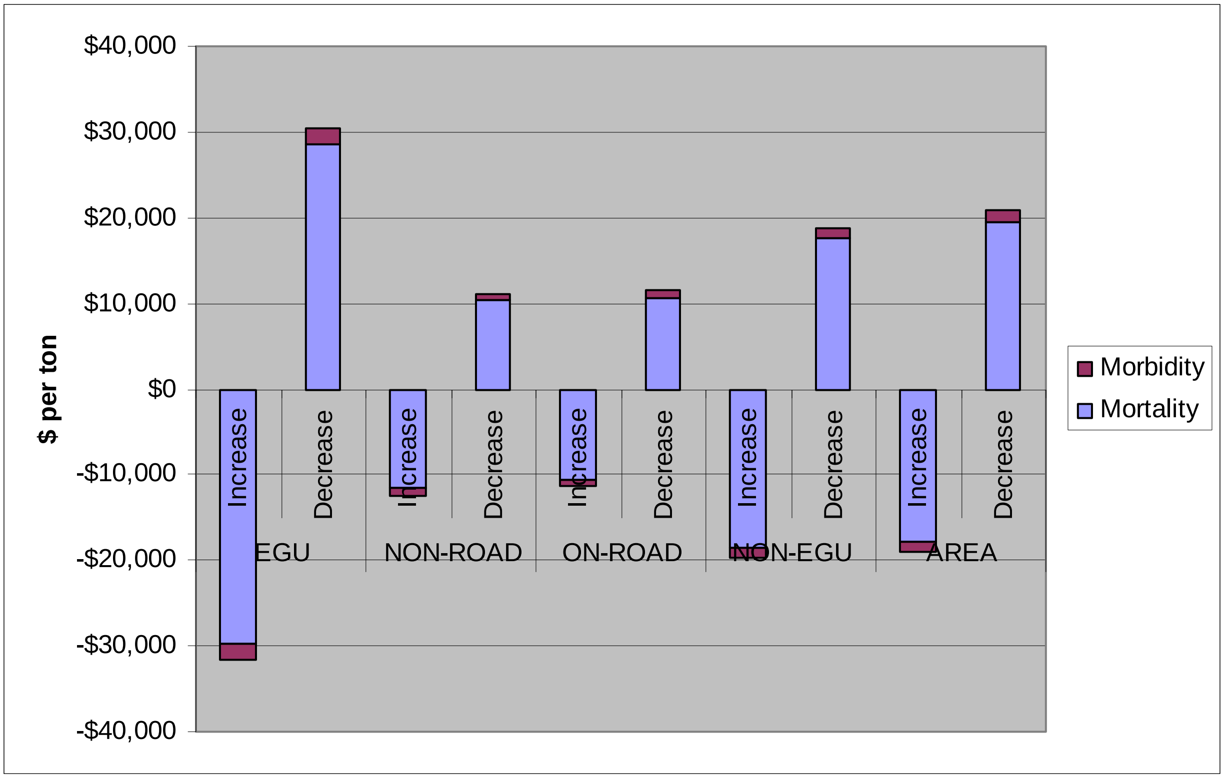
Exhibit 3-8a presents a graph of the dollar per ton benefits associated with a 10 percent change in sector-specific emissions for 2010; Exhibit 3-8b shows comparable results for 2020. Overall, dollar per ton benefits are greater in 2020 than 2010. This means that further reducing emissions yields a greater benefit per ton in 2020 than 2010. Conversely, increasing emissions in 2020 leads to greater damages per ton than increasing emissions in 2010. In both 2010 and 2020 decreasing EGU-specific emissions has the highest dollar per ton value, followed by Area-specific and then Non-EGU specific. In 2010, decreasing Non-road-specific emissions has a higher dollar per ton value than on-road-specific, but the opposite is true in 2020.

EXHIBIT 3-8A MEAN DOLLAR PER TON DAMAGES/BENEFITS ARISING FROM A 10% INCREASE/DECREASE IN SECTOR SPECIFIC EMISSIONS IN 2010 (2006$)



[24] U.S. Environmental Protection Agency. Technical Support Document: Calculating Benefit Per-ton Estimates. Final Ozone Regulatory Impact Analysis.

EXHIBIT 3-8B MEAN DOLLAR PER TON DAMAGES/BENEFITS ARISING FROM A 10% INCREASE/DECREASE IN SECTOR SPECIFIC EMISSIONS IN 2020 (2006$)

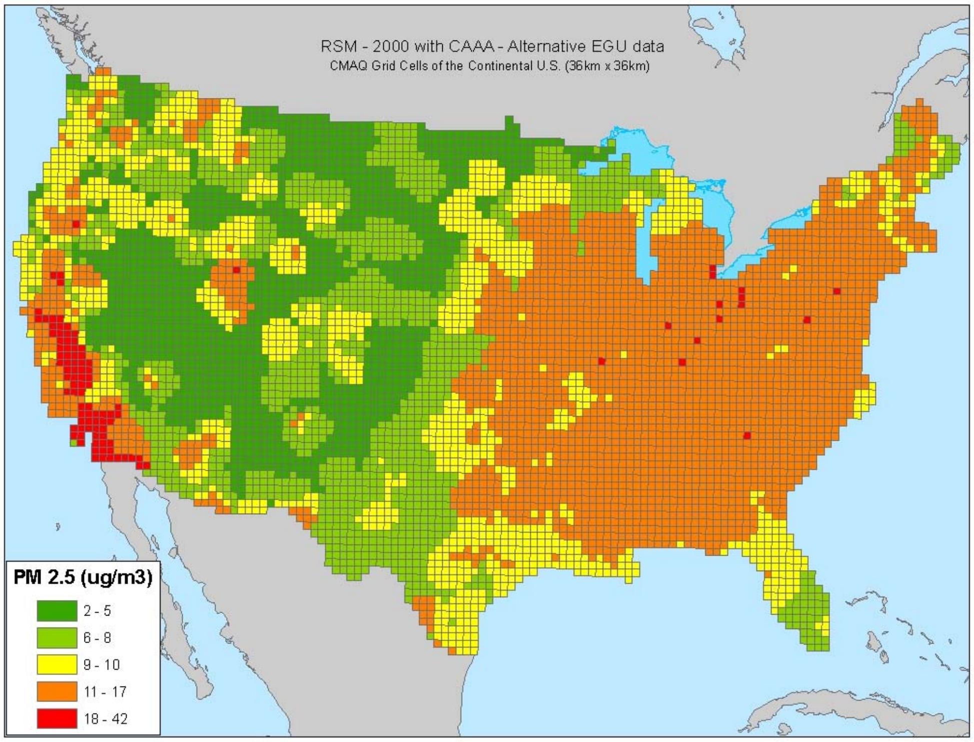


3.4.3 ALTERNATIVE EGU EMISSION SCENARIOS

Exhibit 3-9 depicts the PM RSM results for the 2000 alternative EGU scenarios, and Exhibit 3-10 shows the differences in PM RSM estimated air quality between the primary and alternative EGU emissions estimation methods. The results in Exhibit 3-9 using the alternative EGU data appear very similar to the results using the IPM EGU data, but the difference maps indicate that overall and on average $PM_{2.5}$ concentrations are slightly lower using the CEM data for the *with-CAAA* scenario in 2000, and slightly higher using the data derived using the Ellerman counterfactual method for the *without-CAAA* scenario compared to the corresponding core scenarios.

These results carry over into the benefits calculations. Exhibit 3-11 provides summary BenMAP results for the alternative EGU scenarios, and provides a comparison of the mean BenMAP incidence and valuation results for the 2000 core scenario and the 2000 scenario using the alternative EGU data. This exhibit shows that the health benefits of the CAAA in 2000 estimated with the alternative EGU emissions are approximately 50 percent greater than the benefits in the 2000 core scenario. This result is consistent with the PM RSM results.

EXHIBIT 3-9 ALTERNATIVE EGU EMISSION SCENARIOS PM RSM RESULTS



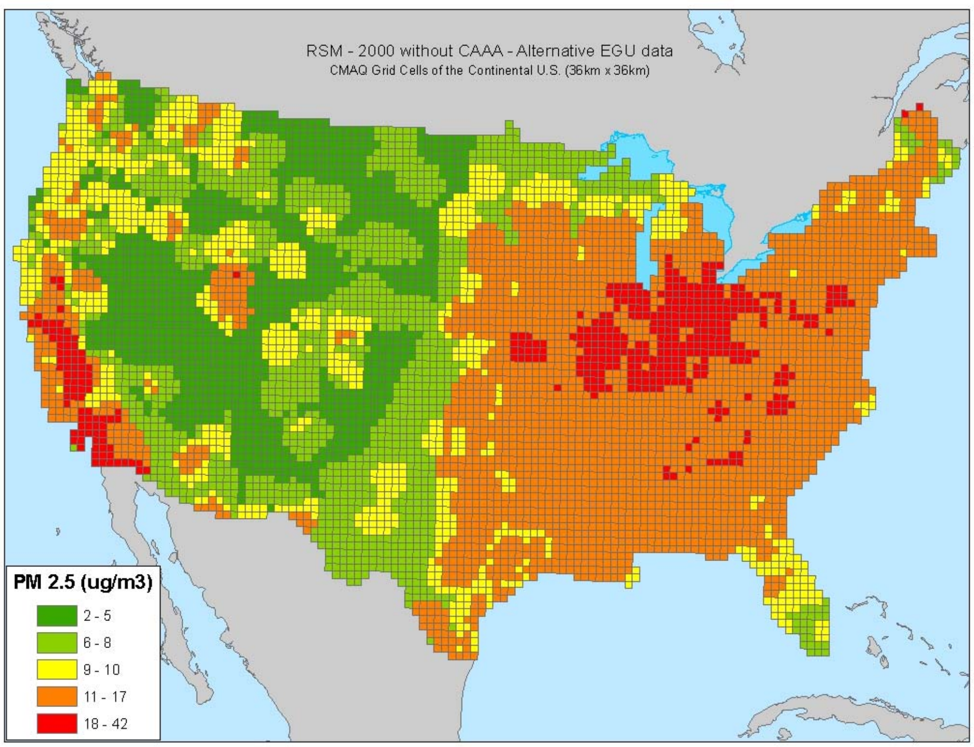
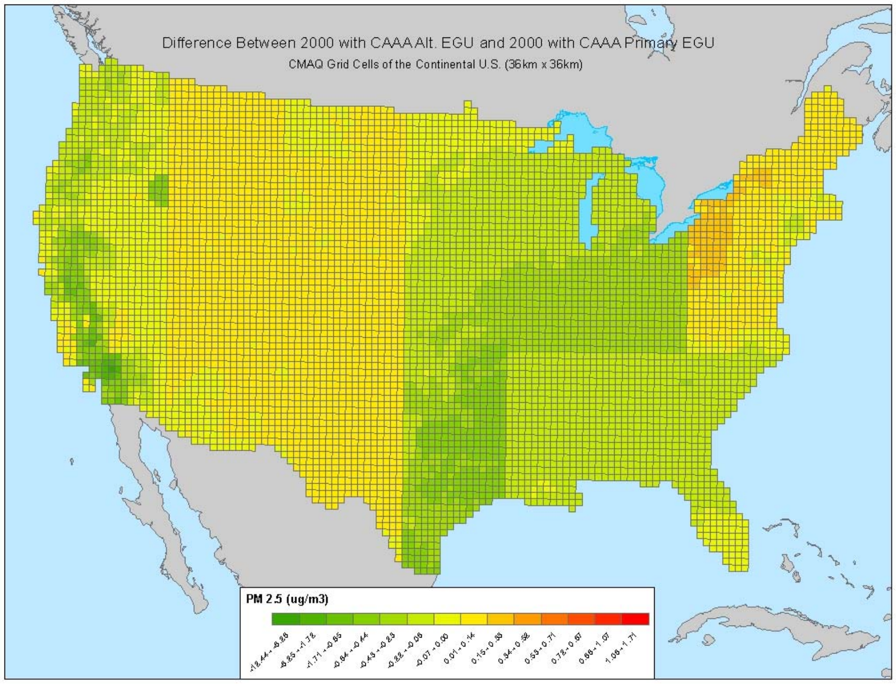


EXHIBIT 3-10 DIFFERENCE BETWEEN ALTERNATIVE EGU AND PRIMARY EGU RSM REULTS



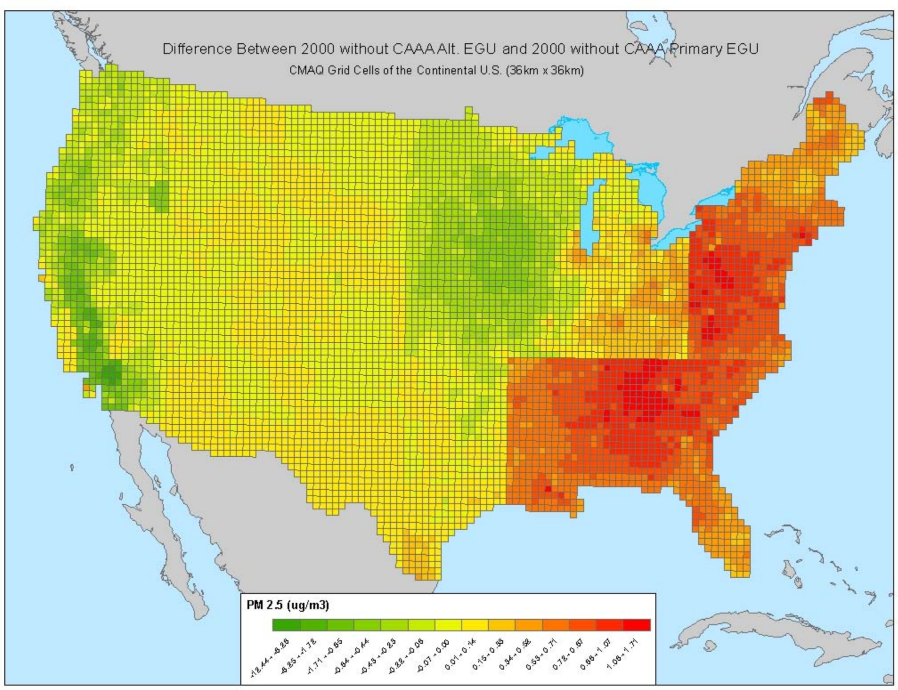


EXHIBIT 3-11 COMPARISON OF MEAN VALUES FOR 2000 CORE AND ALTERNATIVE EGU SCENARIOS

ENDPOINT GROUP	2000 CORE SCENARIO		2000 ALTERNATIVE EGU SCENARIO		PERCENT DIFFERENCE
	INCIDENCE	VALUATION (MIL 2006$)	INCIDENCE	VALUATION (MIL 2006$)	VALUATION
Mortality					
Mortality – Pope et al., 2002	12,300	$83,100	18,600	$125,000	50.4%
Morbidity					
Infant Mortality – Woodruff et al, 1997	33	$252	48	$368	46.0%
Chronic Bronchitis	7,250	$2,990	10,700	$4,410	47.5%
Nonfatal Myocardial Infarction	17,400	$1,780	25,900	$2,650	48.9%
Hospital Admissions, Respiratory	2,770	$38.6	4,210	$58.7	52.1%
Hospital Admissions, Cardiovascular	5,340	$153	8,200	$238	55.6%
Emergency Room Visits, Respiratory	13,000	$4.79	19,300	$7.12	48.6%
Acute Bronchitis	21,200	$9.23	30,200	$13.1	41.9%
Lower Respiratory Symptoms	255,000	$4.69	365,000	$6.70	42.9%
Upper Respiratory Symptoms	196,000	$6.01	282,000	$8.63	43.6%
Asthma Exacerbation	230,000	$11.8	330,000	$16.9	43.2%
Minor Restricted Activity Days	9,420,000	$557	13,900,000	$820	47.2%
Work Loss Days	1,620,000	$244	2,380,000	$359	47.1%
TOTAL		**$89,200**		**$134,000**	**50.2%**

Note: These mortality benefits results are based on the PM-mortality C-R function from Pope et al. (2002) rather than the primary estimate (Weibull distribution) used in the integrated and benefits reports as well as in the remainder of this report. In addition, these results have not been adjusted using the PM adjustment factors to correct analytical issues affecting the $PM_{2.5}$ concentration values. However, these results are intended to provide a relative comparison between the core and alternative EGU scenarios using RSM, rather than absolute benefits results.

3.5 DISCUSSION

The sector scenario results suggest the following broad conclusions:

- The marginal benefits of additional reductions are greatest in the EGU, non-EGU point source, and area source emitting sectors, largely because the pollutant mix in those sectors yields a high benefit per ton of pollutant reduced.

- The spatial pattern of emissions, and therefore of proportional emissions reductions, across major emitting sectors show some differences, but they are not dramatic. The maps in Exhibit 3-6 indicate that, in 2020, most of the remaining emissions remain concentrated in the Northeast and in California, with non-EGU emissions concentrating more in the Southeast, and nonroad emissions concentrated in the agriculturally oriented North Central and California areas of the country.

- Benefits per ton of emissions across all sectors are higher in 2020 than 2010. The reason appears to be that, for all sectors, the *with-CAAA* emissions mix in 2020 includes a higher percentage of direct particulate emissions (POC and PEC) than in 2010. Other EPA analyses conducted with PM RSM have suggested that reductions of directly emitted particulates have a higher benefit per ton than other reductions of other pollutants.

- The shape of the marginal benefits curves across sectors are generally flat for the EGU and non-EGU sectors, somewhat positive for the non-road and onroad sectors, and much more positive for the area source sector. The shape of marginal pollutant response curves in PM RSM can differ dramatically across pollutants, across space, and across levels of pollutant emissions. The reason marginal benefits of pollutant reduction exceed marginal damages of pollutant increases for the area source sector may therefore be a complex combination of factors. Further analysis of the reasons underlying these marginal benefits results could yield further policy-relevant insights that could be used to target future emissions strategies beyond the "on the books" CAAA regulations that are the subject of the second prospective.

- For the alternative EGU emissions scenarios, the substantial, 50 percent difference in air quality outcomes and benefits results is the result of our construction of a substantially different *without-CAAA* scenario. The original motivation of the analysis was concern that the spatial pattern of emissions for the *with-CAAA* scenario for 2000 predicted by an IPM run for a historical year differed from the spatial pattern observed in the emissions monitor data for the same year. Exhibits 3-9 through 3-11 above illustrate that the difference in benefits results is instead due primarily to differences in the *without-CAAA* scenario among the two alternative scenario specifications. The result probably suggests that IPM performs reasonably well in estimating the 2000 *with-CAAA* scenario, but it appears uncertainty in estimating a counterfactual scenario is much larger than uncertainty in estimating the factual case. While we can clearly conclude that the alternative counterfactuals assumptions have a large effect on results, we are left without a clear answer to the question of which method of estimating emissions without the CAAA regulations in place is superior.

CHAPTER 4 | CONCENTRATION-RESPONSE FUNCTION UNCERTAINTY

4.1 INTRODUCTION

One key source of uncertainty in Clean Air Act Amendment (CAAA)-related avoided mortality estimates is the true shape and slope of the concentration-response (C-R) function linking air pollutant exposures with premature mortality. Since the completion of the First Prospective Study, significant advances have occurred that allow for a more thorough evaluation of uncertainties in both particulate matter (PM) and ozone mortality C-R. On the PM side, follow-up studies for both the American Cancer Society (ACS) (Pope et al., 2002) and Six Cities (Laden et al., 2006) cohorts have enhanced our understanding of the potential mortality impacts of changes in annual fine PM (i.e., $PM_{2.5}$) exposures over broad geographical areas.[25,26] In addition, EPA's 12-expert PM-mortality expert elicitation (EE) study provided EPA with 12 comprehensive probabilistic characterizations of statistical, methodological, and scientific uncertainties in the PM-mortality relationship.[27] On the ozone side, advances include the growing literature linking short-term ozone exposures with mortality, including multi-city studies (Schwartz, 2005; Bell et al., 2004; Huang et al., 2005) and three meta-analyses (Ito et al., 2005; Levy et al., 2005; Bell et al., 2005); a cohort study examining long-term effects of ozone (Jerrett et al., 2009); and the 2008 National Research Council (NRC) review.[28,29,30,31,32,33,34,35] The Project Team assessed the sensitivity of the Second

[25] Pope, CA III, et al. (2002). Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. *JAMA* 287: 1132-1141.

[26] Laden, F., J. Schwartz, et al. (2006). Reduction in Fine Particulate Air Pollution and Mortality: Extended Follow-up of the Harvard Six Cities Study. *American Journal of Respiratory and Critical Care Medicine* 173: 667-672.

[27] Industrial Economics, Inc. (2006). *Expanded Expert Judgment Study of the Concentration-Response Relationship Between $PM_{2.5}$ Exposure and Mortality*. Prepared for the Office of Air Quality Planning and Standards, U.S. Environmental Protection Agency, September.

[28] Ito, K., S. F. De Leon and M. Lippmann, 2005. Associations between ozone and daily mortality: analysis and meta-analysis. Epidemiology. Vol. 16 (4): 446-57.

[29] Schwartz, J., 2005. How sensitive is the association between ozone and daily deaths to control for temperature? Am J Respir Crit Care Med. Vol. 171 (6): 627-31.

[30] Bell, M.L., et al., 2004. Ozone and short-term mortality in 95 US urban communities, 1987-2000. Jama, 2004. 292(19): p. 2372-8.

[31] Bell, M. L., F. Dominici and J. M. Samet, 2005. A meta-analysis of time-series studies of ozone and mortality with comparison to the national morbidity, mortality, and air pollution study. Epidemiology. Vol. 16 (4): 436-45.

[32] Levy, J. I., S. M. Chemerynski and J. A. Sarnat, 2005. Ozone exposure and mortality: an empiric bayes metaregression analysis. Epidemiology. Vol. 16 (4): 458-68.

Prospective 812 estimates of PM- and ozone-related mortality incidence to C-R function uncertainty by substituting alternative PM and ozone C-R functions in BenMAP and reanalyzing benefits with the core scenario CMAQ air quality grids for each target year.[36]

4.2 SELECTION OF ALTERNATIVE C-R FUNCTIONS

4.2.1 PARTICULATE MATTER CONCENTRATION-RESPONSE FUNCTIONS

The primary estimate of the second prospective study is based on a Weibull distribution of C-R coefficients with a mean of 1.06 percent decrease in annual all-cause mortality per 1 $\mu g/m^3$ and an interquartile range bracketed by the Pope et al. (2002) ACS estimate (0.55 percent) on the low end and the Six Cities Laden et al. (2006) extended follow-up estimate (1.5 percent) at the high end.[37] We conducted a sensitivity analysis by first substituting the primary C-R distribution with two alternative C-R functions, one based on the Pope et al. (2002) ACS study and the other based on the Laden et al. (2006) Six Cities cohort study. In addition, we used results from the *Expanded Expert Judgment Assessment of the Concentration-Response Relationship Between $PM_{2.5}$ Exposure and Mortality*. This EE study obtained from a panel of 12 leading experts in the field their subjective judgment of the true C-R function relating exposure to $PM_{2.5}$ and mortality in the US. Exhibit 4-1 presents each expert's C-R function uncertainty distribution. We generated 12 estimates of CAAA-related avoided mortality incidence based on the C-R distributions provided by each of the 12 EE study experts.

---

[33] Huang, Y., F. Dominici and M. L. Bell, 2005. Bayesian hierarchical distributed lag models for summer ozone exposure and cardio-respiratory mortality. Environmetrics. Vol. 16: 547–562.

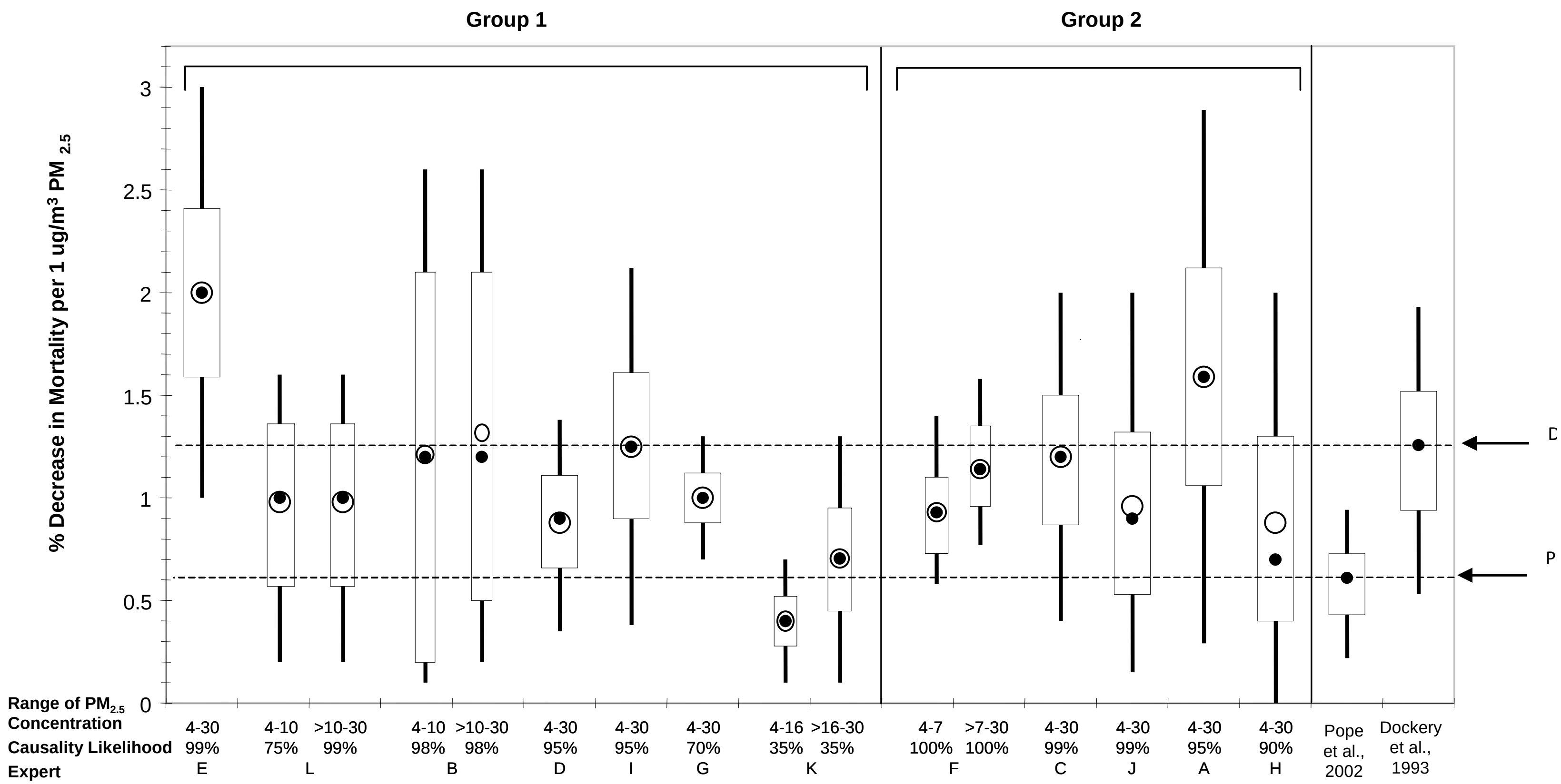
[34] Jerrett M. et al., 2009. Long-term Ozone Exposure and Mortality. JAMA 360 (11): 1085-1095.

[35] National Research Council of the National Academies, 2008. Estimating Mortality Risk Reduction and Economic Benefits from Controlling Ozone Air Pollution. Committee on Estimating Mortality Risk Reduction Benefits from Decreasing Tropospheric Ozone Exposure, Board on Environmental Studies and Toxicology, Division on Earth and Life Studies. National Academies Press, Washington, D.C.

[36] The alternate C-R functions used in our analysis are programmed into BenMAP, as explained in the BenMAP manual in Appendices F and G (Abt Associates, Inc. (2008). BenMAP User's Manual. Prepared for the U.S. EPA's Office of Air Quality Planning and Standards, Research Triangle Park, NC. September).

[37] The parameters for the Weibull distribution are mean = 0.0106, α = 0.0119, and β = 1.622173.

EXHIBIT 4-1. UNCERTAINTY DISTRIBUTIONS FOR THE $PM_{2.5}$-MORTALITY C-R COEFFICIENT FOR ANNUAL AVERAGE $PM_{2.5}$ CONCENTRATIONS OF 4 TO 30 $\mu g/m^3$



Key: Closed circle = median; Open circle = mean; Box = interquartile range; Solid line = 90% credible interval

Note: Box plots represent distributions as provided by the experts to the elicitation team. Experts in Group 1 preferred to give conditional distributions and keep their probabilistic judgment about the likelihood of a causal or non-causal relationship separate. Experts in Group 2 preferred to give distributions that incorporate their likelihood that the $PM_{2.5}$ mortality association may be non-causal. Therefore, the expert distributions from these two groups are not directly comparable.

4.2.2 OZONE CONCENTRATION-RESPONSE FUNCTIONS

The primary estimate used to quantify CAAA-related reductions in ozone-related mortality in the integrated report is a pooled estimate that equally weights the C-R functions from six short-term ozone mortality studies, three of which are meta-analyses (Ito et al., 2005; Levy et al., 2005; Bell et al., 2005), and three of which are individual studies reporting estimates based on data from multiple cities (multi-city studies). Two of the multi-city estimates are derived from the National Morbidity, Mortality, and Air Pollution Study (NMMAPS) (Bell et al., 2004 and Huang et al., 2005) and one is an analysis of 14 U.S. cities (Schwartz, 2005).

We generated results for seven alternative ozone/mortality C-R functions to compare with our primary pooled estimate. Exhibit 4-2 summarizes the ozone mortality C-R functions included in our uncertainty analysis. The first six generate estimates of CAAA-related avoided mortality incidence based on each of the six short-term ozone mortality studies included in the pooled primary estimate. The seventh estimate is based on the results of a recent analysis of the ACS cohort (Jerrett et al., 2009), as recommended by the Council Health Effects Subcommittee (HES).[38] Exhibit 4-2 indicates the type of study, the geographic scope, the specific type of mortality examined, the averaging time of the estimate and the percent change in mortality per 10-ppb change in ozone.

[38] U.S. Environmental Protection Agency Advisory Council on Clean Air Act Compliance Analysis, Health Effects Subcommittee (2010). Review of EPA's Draft Health Benefits of the Second Section 812 Prospective Study of the Clean Air Act, EPA-COUNCIL-10-001, June 16, 2010, available at http://yosemite.epa.gov/sab/sabpeople.nsf/WebCommittees/COUNCIL.

EXHIBIT 4-2. OZONE/MORTALITY CONCENTRATION-RESPONSE FUNCTIONS INCLUDED IN 812 UNCERTAINTY ANALYSIS

	STUDY TYPE	GEOGRAPHIC COVERAGE	HEALTH ENDPOINT	AVERAGING TIME	PERCENT CHANGE IN MORTALITY PER 10 PPB CHANGE IN OZONE
Ito et al. (2005)	Meta-analysis of short-term Studies	43 U.S. and international studies	Non-accidental mortality	8-hour max from 24-hour mean for warm season	1.17%[a]
Levy et al. (2005)	Meta-analysis of short-term studies	28 U.S. and international studies	All-cause mortality	8-hour max from 1-hour max for warm season	1.12%[b]
Bell et al. (2005)	Meta-analysis of short-term studies	39 U.S. and international studies	All-cause mortality	8-hour max from 24-hour mean for warm season	0.80% [c]
Schwartz (2005)	Short-term study	14 U.S. cities	Non-accidental mortality	8-hour max from 1-hour max for warm season	0.43% [d]
Bell et al. (2004)	Short-term study	95 U.S. cities from NMMAPS	Non-accidental mortality	8-hour max from 24-hour mean for warm season	0.26% [e]
Huang et al. (2005)	Short-term study	19 U.S. cities from NMMAPS	Cardiopulmonary mortality	8-hour max from 24-hour mean for warm season	0.81% [f]
Jerrett et al. (2009)	Long-term cohort (analysis of the ACS cohort)	86 U.S. metropolitan statistical areas (MSAs)	Respiratory mortality	8-hour max from 1-hour max for warm season	4.47%[g]

Note: All estimates have been converted to an 8-hour max using ratios of 8-hour max to either 24-hour mean or 1-hour max. See the BenMAP manual for further details (USEPA, 2008).

[a] This estimate represents the combined random-effects estimate for warmer seasons (see page 448 of Ito et al., 2005).

[b] This estimate is based on the single-pollutant grand mean for summer (see page 462 of Levy et al., 2005).

[c] This estimate represents the total mortality effects for U.S. and non-U.S. locations for warmer time periods (see Table 6 of Bell et al., 2005).

[d] This estimate represents the results using the temperature-matched controls for the warm season (see Table 2 of Schwartz, 2005).

[e] This estimate represents the results generated with the constrained distributed-lag model for all communities for days from April to October (see page 2376 of Bell et al., 2004).

[f] This estimate represents the results using summer ozone levels over the previous week (see page 554 of Huang et al., 2005).

[g] This estimate is from the two-pollutant model, which also included particulate matter ($PM_{2.5}$) (Table 3 in Jerrett et al., 2009).

4.3 RESULTS

We present below the results of the alternative C-R function analyses, first for PM and then for ozone.

4.3.1 EFFECTS OF ALTERNATIVE PM CONCENTRATION-RESPONSE FUNCTIONS

Exhibit 4-3 presents the incidence results using the primary C-R function for PM mortality for each target year (2000, 2010, and 2020) as well as the relative changes in mortality incidence associated with using the alternative C-R functions (Pope et al., 2002; Laden et al., 2006; and the EE study results). Exhibit 4-4 compares box plots of the primary and alternative results distributions. These two exhibits show the following:

- The mean benefits estimates generated from the Pope et al. (2002) study are 44 percent lower than the primary estimate, while the Laden et al. (2006) study results are roughly 40 percent higher, due to the difference in the magnitude of the relative risks (RRs) from these two studies.
- The mean estimates of annual avoided deaths due to CAAA generated from the PM EE results vary by expert and range between 83 percent lower than the mean primary estimate up to 76 percent higher at the extremes. The rest of the estimates are within approximately 40 percent or less of the primary estimate.
- As shown in Exhibit 4-4, the spread of the confidence bounds of the alternative C-R function estimates of avoided mortality results vary, with the largest spread found in the distribution provided by Expert A from the EE study and the smallest spread associated with the Pope et al., 2002, which only estimates statistical uncertainty. However, there is some overlap between the confidence bounds of all of the alternate C-R functions, implying that the results are not all statistically significantly different from each other.

4.3.2 EFFECTS OF ALTERNATIVE OZONE CONCENTRATION-RESPONSE FUNCTIONS

Exhibit 4-5 presents changes in mortality incidence based on the primary C-R function for ozone mortality for each target year (2000, 2010, and 2020), as well as the relative changes in mortality incidence associated with using the alternative C-R functions. Exhibit 4-6 is a box plot that illustrates the primary and alternative results distributions. These exhibits show the following:

- The mean benefits estimates generated from the Levy et al. (2005) study are the largest; they are roughly 66 percent higher than the primary estimate, though these are very similar to the Ito et al. estimates. The mean benefits estimates generated from the Bell et al. (2004) study are the lowest, roughly 63 percent lower than the primary estimate.
- In general, the results derived from the three meta-analyses (Ito et al. (2005), Levy et al. (2005), Bell et al. (2005)) are greater than the results derived from three multi-city studies (Schwartz (2005), Bell et al. (2004), Huang et al. (2005)). The results derived from Jerrett et al. (2009) are similar to the results derived

from the meta-analyses and greater than the results derived from the NMMAPS-based studies.[39]

- As shown in Exhibit 4-6, the spread of the confidence bounds of the alternative C-R function estimates incidence results vary, with the largest spread found in the distribution associated with Jerrett et al. (2009) and the smallest spread associated with Bell et al. (2004). The distribution associated with Jerrett et al. (2009) is very similar to that of our primary estimate (the pooling of all six studies). There is some overlap between the confidence bounds of all of the alternate C-R functions, implying that the results are not all statistically significantly different from each other.

EXHIBIT 4-3. ALTERNATIVE C-R FUNCTION MORTALITY INCIDENCE RESULTS FOR $PM_{2.5}$

MORTALITY C-R FUNCTION	PERCENTILE 5	MEAN	PERCENTILE 95
Primary Estimate - 2000	**20,000**	**110,000**	**230,000**
Primary Estimate - 2010	**31,000**	**160,000**	**350,000**
Primary Estimate - 2020	**44,000**	**230,000**	**480,000**
	Percent Change from Mean Primary Estimate		
Pope et al. (2002)	-77%	-44%	-11%
Laden et al. (2006)	-22%	40%	98%
Expert A	-71%	38%	150%
Expert B	-87%	1%	95%
Expert C	-59%	10%	79%
Expert D	-95%	-21%	28%
Expert E	-9%	76%	156%
Expert F	-41%	-9%	24%
Expert G	-100%	-34%	20%
Expert H	-100%	-21%	83%
Expert I	-90%	10%	83%
Expert J	-86%	-11%	83%
Expert K	-100%	-83%	-24%
Expert L	-99%	-28%	24%
Note: All values in the table represent the percent change from the mean primary estimate. Percent change estimates do not vary by target year.			

[39] Although the coefficient from the study is much higher than those reported in the meta-analyses or multi-city studies, the endpoint is restricted to respiratory mortality and therefore the avoided mortality results are similar to the meta-analyses, which are based on non-accidental or all-cause mortality.

EXHIBIT 4-4. BOX-PLOT OF 90 PERCENT CONFIDENCE BOUNDS FOR ALTERNATIVE C-R FUNCTION MORTALITY INCIDENCE

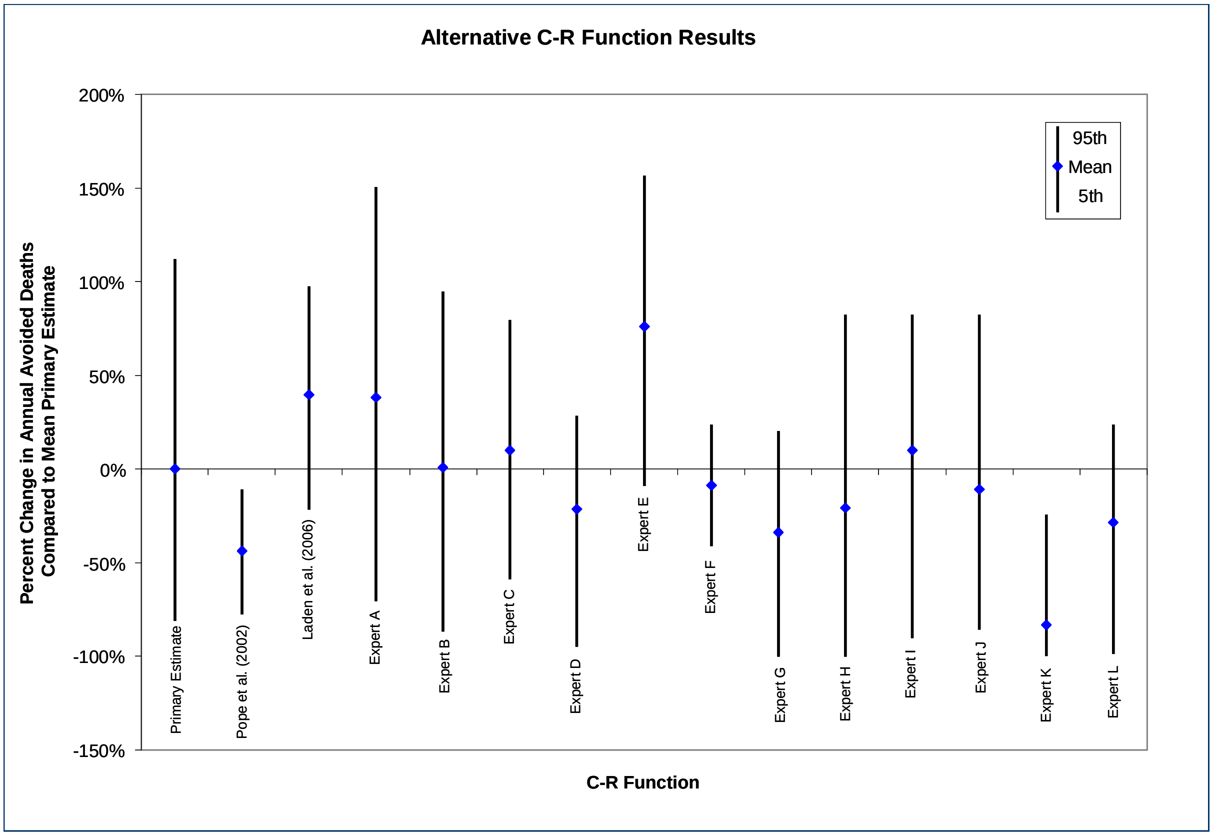
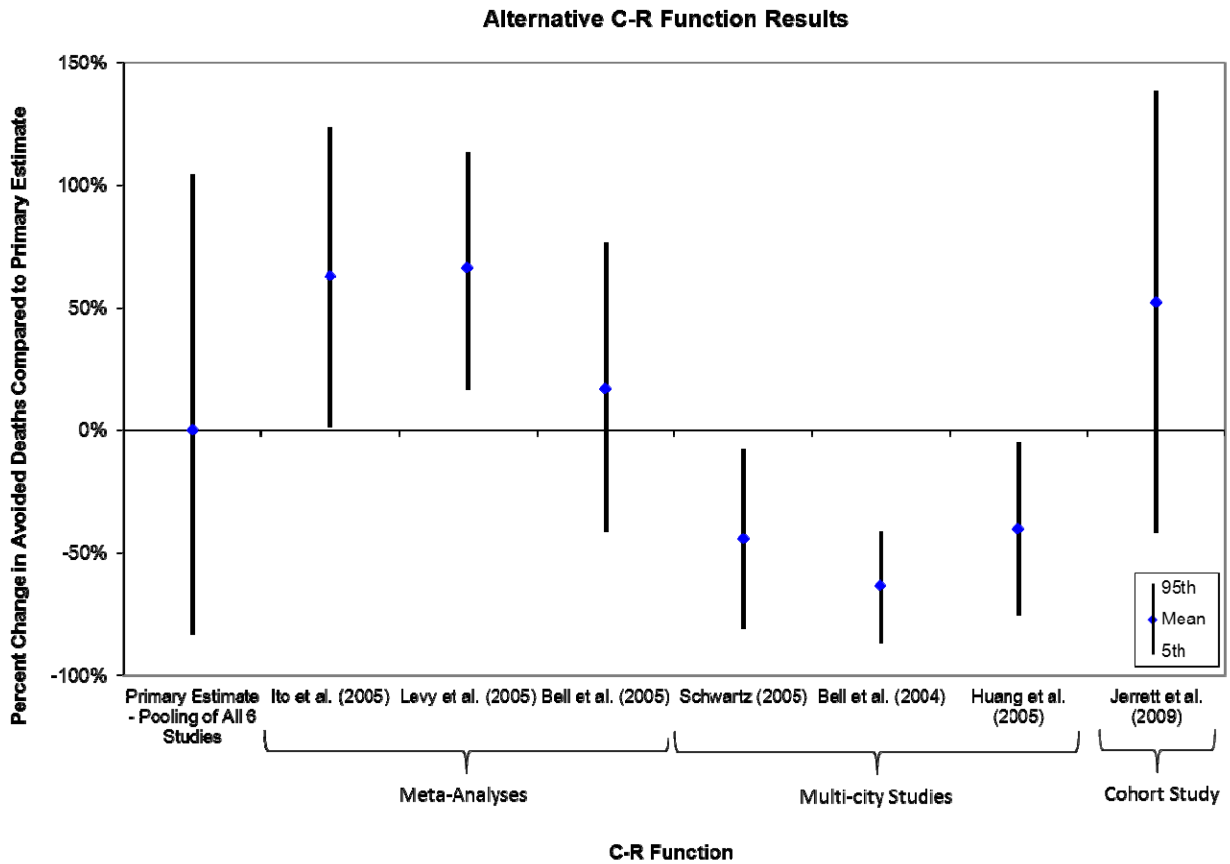


EXHIBIT 4-5. ALTERNATIVE C-R FUNCTION MORTALITY INCIDENCE RESULTS FOR OZONE

MORTALITY C-R FUNCTION	PERCENTILE 5	MEAN	PERCENTILE 95
Primary Estimate - 2000	210	1,400	2,800
Primary Estimate - 2010	790	4,300	8,700
Primary Estimate - 2020	1,200	7,100	15,000
	Percent Change from Mean Primary Estimate		
Meta-Analyses (short-term)			
Ito et al. (2005)	1%	63%	123%
Levy et al. (2005)	17%	66%	113%
Bell et al. (2005)	-41%	17%	76%
Multi-City Studies (short-term)			
Schwartz (2005)	-81%	-45%	-8%
Bell et al. (2004)	-87%	-63%	-41%
Huang et al. (2005)	-75%	-40%	-5%
Cohort Study (long-term)			
Jerrett et al. (2009)	-41%	52%	138%
Note: Incidence results are rounded to two significant figures.			

EXHIBIT 4-6. BOX-PLOT OF THE 90 PERCENT CONFIDENCE BOUNDS FOR ALTERNATIVE C-R FUNCTION RESULTS FOR OZONE



CHAPTER 5 | DIFFERENTIAL TOXICITY OF PM COMPONENTS[40]

5.1 INTRODUCTION

In the current 812 prospective analysis, EPA estimates particulate matter (PM)-related health benefits using functions that relate these effects with changes in $PM_{2.5}$ or PM_{10} as a whole, measured as the total mass of particles. This approach is consistent with historical EPA practice and with past Advisory Council for Clean Air Compliance Analysis (Council) advice (see below). However, the mass of PM includes a number of different components, and these components may vary in their toxicity and therefore in the degree to which they contribute to the mortality and other adverse health effects observed in the epidemiological literature. The assumption that all particle components have identical toxicity (or, for that matter, any assumption regarding the relative toxicity of various particle components without a strong empirical basis) may introduce bias to estimates of health benefits, if the health benefits of PM reductions depend specifically on the types of particles being reduced. More generally, even if no systematic biases can be identified, the issue of differential toxicity contributes to increased uncertainty in the estimates of health benefits.

It is important to recognize that our ability to address the issue of differential toxicity in quantitative health benefits analysis is limited for a variety of reasons. While some of the limitations will likely decrease over time given improvements in scientific understanding, others are intrinsic to the question and will remain. Specifically, while increasing availability of speciation network data allow for epidemiological studies addressing individual components, many components covary in the atmosphere to such a degree that it would make it difficult to separate their effects. In some respects, this issue is a variant of an issue that EPA has addressed successfully in other settings, when attempting to separate the health effects of individual criteria pollutants from one another based on epidemiological evidence. However, the case of PM components extends beyond this domain (which is generally addressed through a combination of multivariate statistical analyses and study designs/locations that help to isolate the effects of individual pollutants), as particles in the atmosphere are often complex agglomerations of a variety of components. This indicates that the topic of differential toxicity is not only a statistical issue, but also a physical interpretability issue. The composition of the atmosphere also varies considerably over time and space, making it challenging to determine (for example) whether a reduction in sulfate concentrations in Massachusetts in 2010 is

[40] We gratefully acknowledge the substantial contributions of Dr. Jonathan Levy of the Harvard School of Public Health in the development and review of this chapter.

functionally equivalent to the same unit reduction in sulfate concentrations in California in 2020. These and other limitations are discussed in more detail below.

From a practical standpoint, the relevant question is whether uncertainty related to differential toxicity would be significant enough in magnitude to invalidate results of benefits analyses. While this uncertainty could be substantial for control strategies only addressing a single component on the margin, many control measures under consideration by EPA are "blended" strategies addressing multiple PM sources and components simultaneously, which will tend to reduce errors in the aggregate benefits estimates.

This chapter describes some of the significant questions and challenges that remain to be addressed before differential toxicity could be meaningfully introduced into benefits analysis, either through adjustments to component-specific concentration-response (C-R) functions or through addition of uncertainty analyses that go beyond hypothetical "what if" scenarios. Currently, EPA and its Council support the use of PM mass as the most defensible means of estimating benefits and believe the results of any uncertainty analysis should be interpreted with caution. While we agree that the use of PM mass remains the most defensible strategy and that there is neither an empirical nor logical basis for incorporating quantitative differential toxicity at this time, in this chapter, we formally evaluate the evidence for differential toxicity, considering the nature of the evidence that would be required to address this topic and the way in which this evidence would need to be structured and analyzed. This discussion is intended to explore the approaches that can be taken to quantify differential toxicity and the challenges in conducting such analyses.

The remainder of this chapter reviews how this issue has been addressed in past 812 analyses, discusses the importance of this uncertainty and the nature of the evidence needed to incorporate quantitative differential toxicity into benefits analyses, gives a brief overview of our current understanding of the issue, lays out key challenges to a meaningful uncertainty analysis of differential toxicity, and discusses key data gaps that need to be addressed before a policy relevant analysis can be conducted.

5.2 HISTORICAL APPROACH

EPA's approach to estimating avoided mortality and morbidity associated with reductions in fine particles uses estimates of changes in exposure to $PM_{2.5}$ mass as the exposure input in the damage function. The implication of this approach is that we assume that all fine particles, regardless of their chemical composition, are equally potent per unit concentration in producing premature mortality and other health outcomes. More precisely, we assume that the most credible quantitative estimate for policy decision-making involves using the same toxicity value for all fine PM mass components, given an insufficient basis to quantitatively deviate from this assumption. Uncertainty surrounding this assumption is not generally quantified, but is usually discussed.

This approach reflects several considerations. First, it is worth recognizing that there is a biological rationale for a focus on particulate mass below a specified aerodynamic diameter, as size has clearly been demonstrated to influence deposition patterns in the lung, with fine particles penetrating more deeply and being less likely to be cleared than coarser particles. Thus, even if chemical composition has an influence on the resulting toxicity, the size of the particle is clearly important (and, indeed, this is the primary rationale for a regulatory system oriented around particle size).

Second, the equal toxicity approach reflects the consistency of findings in epidemiological studies conducted across countries, states, and cities that $PM_{2.5}$ concentrations are associated with increased mortality and morbidity rates, despite geographic variations in composition. If there were stark differences in the toxicity of various particle components, epidemiological findings would be expected to be far more discordant. For example, time-series studies in the US, Europe, Australia, and Asia have all yielded statistical significant effects of PM on premature mortality (Pope and Dockery 2006), in spite of substantial differences in diesel fuel utilization, coal combustion, and other activities that would influence the chemical composition of fine particles in these varied settings.[41]

Not only are the findings qualitatively similar (with statistical significance in diverse geographic settings), but the C-R functions do not appear to be substantially different across different countries or regions of the US. Meta-analyses and multi-city studies of the PM-mortality literature to date have found some spatial heterogeneity by region, but have not found large systematic differences that would exonerate specific components or support direct quantitative estimation of differential toxicity among specific particle components. For example, the National Morbidity Mortality and Air Pollution Study (NMMAPS) found higher C-R functions for PM_{10} in the Northeast (where sulfates predominate) and in Southern California (which nitrates and organic carbon predominate), relative to other regions (Dominici et al., 2005).[42] A more recent multi-city study of $PM_{2.5}$ morbidity concluded that C-R functions for respiratory and cardiovascular hospital admissions were higher in the Northeast for a same-day effect, but were higher in the Southwest for a two-day lag for respiratory hospital admissions (Bell et al., 2008).[43] More generally, this study concluded that there was significant spatial heterogeneity for cardiovascular but not respiratory hospital admissions. Another multi-city study of $PM_{2.5}$ mortality (Franklin et al., 2007) found higher C-R functions in the East than in the West, but the difference was not significant and was best explained by air conditioning prevalence.[44]

Thus, there do not appear to be stark geographic patterns in C-R functions, making extreme differential toxicity outcomes (e.g., that toxicity is due solely to a single PM component) appear unlikely. Further, any spatial variations in the PM C-R function may

---

[41] Pope, C.A. and Dockery, D.W., 2006. Health Effects of Fine Particulate Air Pollution: Lines that Connect. Air Waste Management Association. Vol. 56: 709-742.

[42] Dominici, F. et al., 2005. Revised Analyses of the National Morbidity, Mortality, and Air Pollution Study: Mortality Among Residents of 90 Cities. Journal of Toxicology and Environmental Health. Vol. 68 (13): 1071-1092)

[43] Bell ML, Ebisu K, Peng RD, Walker J, Samet JM, Zeger SL, Dominici F. 2008. Seasonal and regional short-term effects of fine particles on hospital admissions in 202 US counties, 1999–2005. Am J Epidemiol Vol. 168:1301–1310.

[44] Franklin M, Zeka A, Schwartz J. 2007. Association between $PM_{2.5}$ and all-cause and specific-cause mortality in 27 US communities. J Expo Sci Environ Epidemiol. Vol. 17(3):279-87.

be attributable to factors beyond the chemical composition of the fine particles, including concentration-exposure relationships and vulnerability characteristics. This evidence reinforces the suggestion that an assumption that the same C-R function is applicable to all control strategies (especially blended PM reduction strategies) in all settings is a reasonable one. This evidence also reflects the judgment of EPA and its Council that the research conducted to date does not yet provide sufficiently clear evidence for quantification of particle mortality impacts at a finer level than total $PM_{2.5}$ mass.

The Council has supported this approach in the past two 812 analyses and also in its review of plans for the current analysis, while encouraging EPA to explore the possible implications of differential toxicity uncertainties on results. In its March 2004 review of the analytical blueprint, the 812 Council Health Effect Subcommittee (HES) provided advice to EPA on this issue. First, in response to a charge question regarding a potential expert elicitation initiative on PM mortality that included questions on relative component toxicity, the committee states:

> "Regarding the question of component relative toxicity, the evidence at this time supporting differential toxicities based on particle chemistry is provided by a few studies of short-term exposure (e.g., Laden et al., 2000). Currently, there is little evidence from the long-term exposure studies to suggest differential toxicity. Therefore, it is appropriate at this time for EPA to assume equal toxicity across particle components and it is reasonable to explore alternative possible implications of differential particle component potency in supplementary sensitivity analyses."[45]

The HES commented further on a relative toxicity sensitivity analysis in their response to a charge question on aggregation and presentation of results:

> "There are only a few C-R functions for source-specific health effects and therefore limited information for sector-specific PM health benefits or for apportioning health benefits among sources or sectors other than as a function of source-specific contributions to ambient PM mass. With the exception of particle size considerations, the toxicity of all PM is treated as equivalent regardless of its origin. There is limited evidence (i.e., Laden et. al., 2000) to suggest some differential toxicity of PM, at least regarding mortality and daily PM exposures. If the data are available on source-specific changes in PM, EPA should consider conducting a limited sensitivity analysis utilizing some of this evidence." [46]

[45] U.S. Environmental Protection Agency, Science Advisory Board. 2004. Advisory on Plans for Health Effects Analysis in the Analytical Plan for EPA's Second Prospective Analysis - Benefits and Costs of the Clean Air Act, 1990-2020; Advisory by the Health Effects Subcommittee of the Advisory Council on Clean Air Compliance Analysis. EPA-SAB-COUNCIL-ADV-04-002, page 20.

[46] *Ibid.* page 37.

5.3 IMPORTANCE OF DIFFERENTIAL TOXICITY FOR BENEFITS ANALYSIS

From a benefits analysis perspective, treatment of all $PM_{2.5}$ mass as equally toxic may lead to biases in benefits estimates. Likewise, any arbitrary assumption about the differential toxicities of particle components may also lead to biases in benefits estimates. Any of these biases may mask important spatial variation in the distribution of benefits of Clean Air Act (CAA) programs across the U.S. due to regional variation in PM speciation, which could affect selection of the most health beneficial measures to meet CAA requirements such as the National Ambient Air Quality Standards (NAAQS).

The significance of the uncertainty related to differential toxicity will likely differ substantially by application. An analysis of the entire CAA Amendments or of the benefits of attaining the NAAQS (which would likely use a blended strategy) would likely be affected less by these uncertainties than an analysis of the Clean Air Interstate Rule (CAIR) or non-road diesel rule which focus on more narrow emissions control strategies. Similarly, an analysis of CAIR or other multi-pollutant power plant control strategies would be less uncertain than an analysis of SO_2 controls exclusively. However, even more "narrow" emissions control strategies invariably result in control of multiple pollutants, either by design (e.g., CAIR and the non-road diesel rule each reduced NOx, SO_2, and directly-emitted PM) or due to the nature of the emission reduction strategies that would be implemented, which often do not influence only one pollutant at a time. Even in cases where a single pollutant may be reduced, the ultimate effect on ambient particles is more complicated, because of the complex atmospheric chemistry involved in particle formation. For example, reductions in SO_2 can affect not only sulfate, but also nitrate and ammonium particle levels, and can affect transport and form of metals in particle mixtures.

A focus on benefits analysis also influences the type of evidence that would be necessary to incorporate differential toxicity. Within benefits analysis of fine PM control strategies, C-R functions are developed from epidemiological evidence, reflecting the anticipated change in health outcomes across the human population (including sensitive subpopulations) associated with changes in ambient air pollution levels. As this reflects a population C-R function (a combination of individual functions that reflects variability in individual response thresholds), this captures aspects of human vulnerability to $PM_{2.5}$-related health effects. The ideal study of differential toxicity would therefore be an epidemiological investigation with sufficient information about particle composition and related exposures (varying over both time and space), good characterization of vulnerable populations, and good specificity in health outcomes.

Clearly, toxicological studies are important for determining the health effects of pollutants and for providing an understanding of the biological underpinnings of the associations observed in epidemiological studies. However, in the specific context of differential toxicity for health benefits analysis, it is necessary but not sufficient to establish mechanisms, even if they appear to be differential by component. For toxicological studies to be directly and quantitatively applicable to health benefits analysis, they would need to be conducted in animal populations with disease models that appropriately capture the vulnerable individuals at the lower end of the C-R function; they would need to provide quantitative outputs that can be translated directly into outcomes such as cardiovascular hospital admissions or premature mortality from long-term exposure; and they would need to utilize exposure measures that are directly translatable to the exposure measures used in epidemiological studies, both considering the level of exposure and the type of exposure. Even a toxicological study that uses ambient-derived aerosols in animal models of cardiovascular disease and provides quantitative estimates of effects on heart rate variability or measures of atherosclerosis would not be directly applicable to benefits analysis, given the difficulty in linking high-concentration pre-clinical effects in animals with quantitative low-concentration health outcomes in humans. Moreover, even if models could be developed to link this toxicological insight to the human population, identical translation would need to occur for a variety of mixtures of components, including consideration of the marginal effects of changes in the mixture.

Because of these issues, it is likely that the relative contributions of epidemiology and toxicology would be similar in a differential toxicity analysis as in a benefits analysis for $PM_{2.5}$ as a whole – the quantitative functions would be solely based on epidemiology, with toxicology providing corroboration of biological plausibility and mechanisms of disease, and perhaps eventually contributing to expert opinions within elicitation protocols. More specifically, in the absence of epidemiological evidence for differential toxicity, it would be exceedingly difficult to determine quantitative C-R functions for individual particle components that would be applicable to human populations.

5.4 CURRENT UNDERSTANDING OF DIFFERENTIAL TOXICITY

The following section provides a general overview of the strength of epidemiological and toxicological evidence examining possible differential toxicity of PM components and sources. We first provide an illustrative discussion of some of the key epidemiological and toxicological evidence linking specific PM components to health outcomes and then examine source-oriented evaluations.

5.4.1 COMPONENT-ORIENTED EVALUATIONS

This section briefly reviews the current state of knowledge on the differential toxicity of specific PM components. The aim of this section is not to be exhaustive, but the evidence below does reflect the nature and size of the epidemiological literature on PM components to date.

The major components of PM, some or all of which may contribute to its toxicity, include metals (e.g., iron, vanadium, nickel, copper), organic compounds that are either adsorbed onto other particles or may form particles themselves, biologic elements (e.g., viruses, bacteria), ions such as sulfate (SO_4^{2-}), nitrate (NO_3^-), and acidity (H+), reactive gases (e.g., ozone, aldehydes) adsorbed to particles, and carbonaceous material that constitutes the particle core (HEI, 2002; NRC, 2004).[47,48] Of note, some of the above-mentioned

[47] Health Effects Institute, 2002. Understanding the Health Effects of Components of the Particulate Matter Mix: Progress and Next Steps. Boston, MA.

components are particle components that may be differentially affected by common control strategies (such as sulfate and nitrate particles), while others (such as reactive gases adsorbed to particles or biologic elements) reflect factors that complicate the assessment of differential toxicity for the components conventionally evaluated in a differential toxicity analysis of PM.

A study by Bell et al. (2007) analyzed EPA monitoring data on 52 $PM_{2.5}$ components in 187 U.S. counties between February 2000 and December 2005 to identify $PM_{2.5}$ components that would be important to target in future epidemiological studies.[49] The study found that only seven of the 52 components contributed at least 1 percent to total mass for yearly or seasonal averages. This included ammonium (NH_4^+), elemental carbon (EC), organic carbon matter (OCM), nitrate (NO_3^-), silicon, sodium (Na+), and sulfate (SO_4^{2-}). The study also postulated that in order for a component to be a mediator of the risk associated with total $PM_{2.5}$ mass, the concentration of the component must co-vary with the concentration of $PM_{2.5}$. The authors found six components that met this criterion: NH_4^+, SO_4^{2-}, OCM, NO_3^-, bromine, and EC. Therefore, it is likely that these components would be of greatest interest in explaining the health risks seen from exposure to $PM_{2.5}$ in epidemiological studies.

It is important to recognize that this does not imply that other components would not be toxic or exhibit health effects at current levels of exposure, but rather that the epidemiological findings of health effects of $PM_{2.5}$ could not be explained by components that did not covary with $PM_{2.5}$. While it is not impossible for low-mass components to explain all of the observed effects (if such components were highly toxic and covaried with $PM_{2.5}$), it is also unlikely that the totality of the epidemiological effects could be explained by components that contribute minimal mass. In addition, from a practical standpoint, control strategies to meet the NAAQS would tend to target the high-mass components as the only viable strategies to achieve attainment. Examining the intersection of the high-mass and high-correlation compounds, and considering the fact that ammonium is generally bound to either sulfate or nitrate, this study emphasizes that the primary components of interest would likely include sulfate, nitrate, OCM, and EC. In the context of differential toxicity, the key question is whether the health risks of fine particles can be plausibly apportioned among these (and other) components, in such a way that is consistent with the evidence for $PM_{2.5}$ as a whole.

As a general point, a number of epidemiological studies, mostly time-series studies, have associated one or more of these $PM_{2.5}$ components with mortality, but no clear picture has emerged. The National Research Council (NRC) in its report entitled "Research Priorities for Airborne Particulate Matter" indicated that:

---

[48] National Research Council. 2004. Research Priorities for Airborne Particulate Matter: IV. Continuing Research Progress. National Academies Press: Washington, DC.

[49] Bell, M.L. et al., 2007. Spatial and Temporal Variation in $PM_{2.5}$ Chemical Composition in the United States for Health Effects Studies. Environmental Health Perspectives. Vo. 115(7): 989-995.

> "Although substantial relevant research has been carried out on this topic, the [NRC] committee's review showed a collection of evidence with little convergence … This topic has proved particularly challenging because of the many aspects of particles that might plausibly determine toxicity and the strong possibility that different characteristics of particles could be relevant to different health outcomes."[50]

The following sections provide a brief overview of epidemiological and toxicological evidence regarding the relative toxicity of various PM components, focusing on sulfate, nitrate, OCM, and EC, but also considering metals, which do not contribute substantial mass to the total but remain of interest given evidence about their effects and potential interactions with the high-mass components (e.g., the tendency of metals to bind with sulfates and potentially become more bioavailable).

5.4.1.1 Sulfate

Sulfate is the PM component with the greatest body of literature examining its toxicity to date. Epidemiological studies (both time-series and long-term cohort) as well as toxicological studies have been conducted that include effect estimates for PM and sulfates, allowing (in theory) for assessments that evaluate the toxicity of sulfate relative to the total mass. In a recently published paper reviewing studies on sulfates, Reiss et al. (2007) found 48 risk estimates for $PM_{2.5}$ and sulfate across 11 time-series epidemiological studies.[51] Five of the 11 studies had at least one statistically significant endpoint for sulfate (versus 8 of the 11 studies for $PM_{2.5}$), so from a significance standpoint, the evidence appears weaker for sulfate than for $PM_{2.5}$.

However, statistical significance is only one component of the type of comparison that would be necessary, with the size of the C-R function also being of great interest. Focusing on all-cause mortality, the magnitude of effects with sulfate from the time-series studies reported in Reiss et al. (2007) range from no association up to a relative risk (RR) of 1.2 for a 10 $\mu g/m^3$ change in sulfate, a generally similar range as observed for $PM_{2.5}$ as a whole in those same studies. Taking the eight studies listed in Reiss et al. that had quantified sulfate relative risks and $PM_{2.5}$ relative risks, one can perform an inverse-variance weighted pooling, using methods to account for potential heterogeneity in effect estimates.[52] This results in a pooled central estimate of a 1.2% increase in mortality per 10 $\mu g/m^3$ increase in $PM_{2.5}$ (95% CI: 0.7%, 1.7%) vs. a 2.0% increase in mortality per 10 $\mu g/m^3$ increase in sulfate (95% CI: 0.3%, 3.8%), which shows that sulfate has a higher central estimate than $PM_{2.5}$ as a whole, but with wider confidence intervals (and overlapping confidence intervals for both C-R functions).

Some subsequent time-series studies not included in Reiss et al. (2007) have shown effects of sulfate on mortality (i.e., Maynard et al., 2007; Franklin and Schwartz,

---

[50] National Research Council., *op. cit.*

[51] Reiss, R. et al., 2007. Evidence of Health Impacts of Sulfate-and-Nitrate-Containing Particles in Ambient Air. Inhalation Toxicology. Vol. 19(5): 419-449.

[52] DerSimonian, R., Laird, N. (1986). Meta-Analysis in Clinical Trials. Controlled Clinical Trials, 7: 177-188.

2008).[53,54] A multi-city study examining factors explaining variability in the relationship between $PM_{2.5}$ and mortality concluded that cities with a higher proportion of sulfate (as well as aluminum and nickel) tended to have higher $PM_{2.5}$ C-R functions (Franklin et al., 2008).[55] However, a multi-city study focusing on hospital admissions found no associations between sulfate and either respiratory or cardiovascular admissions (Bell et al., 2009).[56] In addition, panel studies have found associations between short-term exposures to sulfate and markers of cardiovascular disease (e.g., Luttmann-Gibson et al., 2006; Sarnat et al., 2006; and O'Neill et al., 2005).[57,58,59]

Some evidence also exists for an association between mortality and sulfates in long-term cohort epidemiological studies. Positive relative risks for sulfate in relation to all-cause mortality were found in the American Cancer Society (ACS) cohort study (Pope et al., 1995) and its extended analysis (Pope et al., 2002).[60,61] Within the ACS study, the relative risk for sulfate was generally slightly greater than that for $PM_{2.5}$ per unit concentration. Similarly, in the Harvard Six Cities study (Dockery et al, 1993; Krewski et al., 2000), effects for sulfate were similar to those for $PM_{2.5}$ as a whole, with a greater C-R function per unit concentration, although with a smaller number of sites and high correlations between sulfate and $PM_{2.5}$, it would be difficult to separate out the effects.[62,63]

---

[53] Maynard, D., B.A. Coull, A.Gryparis, and J. Schwartz. 2007. Mortality Risk Associated with Short-Term Exposure to Traffic Particles and Sulfates. Environ Health Perspect. Vol. 115(5): 751–755.

[54] Franklin, M. and Schwartz, J. 2008. The Impact of Secondary Particles on the Association Between Ambient Ozone and Mortality. Environ Health Perspect. Vol. 116(4):453-8.

[55] Franklin, M. et al., 2008. The Role of Particle Composition on the Association Between $PM_{2.5}$ and Mortality. Epidemiology. Vol. 19(5): 680-689.

[56] Bell, M.L. et al., 2009. Hospital Admissions and Chemical Composition of Fine Particle Air Pollution. American Journal of Respiratory and Critical Care Medicine. Vol. 179: 1115-1120.

[57] Luttmann-Gibson H, H.H.Suh, B.A. Coull, D.W. Dockery, S.E. Sarnat, J. Schwartz, P.H. Stone, D.R. Gold. 2006. Short-Term Effects Of Air Pollution On Heart Rate Variability In Senior Adults In Steubenville, Ohio. J Occup Environ Med. Vol. 48(8):780-8.

[58] Sarnat SE, H.H. Suh, B.A. Coull, J. Schwartz, P.H. Stone, D.R. Gold. 2006. Ambient Particulate Air Pollution And Cardiac Arrhythmia In A Panel Of Older Adults In Steubenville, Ohio. Occup Environ Med. Vol. 63(10):700-6.

[59] O'Neill, M.S. et al., 2005. Diabetes Enhances Vulnerability to Particulate Air Pollution-Associated Impairment in Vascular Reactivity and Endothelial Function. Circulation. Vol. 111: 2913-2920.

[60] Pope, C.A., III, M.J. Thun, M.M. Namboodiri, D.W. Dockery, J.S. Evans, F.E. Speizer, and C.W. Heath, Jr., 1995. "Particulate Air Pollution as a Predictor of Mortality in a Prospective Study of U.S. Adults." American Journal of Respiratory Critical Care Medicine 151:669-674.

[61] Pope, CA III, et al. (2002). Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. *JAMA* 287: 1132-1141.

[62] Dockery, D.W., C.A. Pope, X.P. Xu, J.D. Spengler, J.H. Ware, M.E. Fay, B.G. Ferris, and F.E. Speizer, 1993. "An Association between Air Pollution and Mortality in Six U.S. Cities." New England Journal of Medicine 329(24):1753-1759.

[63] Krewski D., R.T. Burnett, M.S. Goldbert, K. Hoover, J. Siemiatycki, M. Jerrett, M. Abrahamowicz, and W.H. White, July 2000. Reanalysis of the Harvard Six Cities Study and the American Cancer Society Study of Particulate Air Pollution and Mortality. Special Report to the Health Effects Institute, Cambridge MA.

Thus, the epidemiological evidence to date appears supportive of an effect of sulfate particles on health outcomes, with modest but inconsistent evidence that the C-R functions per unit concentration may be slightly greater than for $PM_{2.5}$ as a whole. However, these results have not generally been supported by the toxicological database consisting of controlled animal and human clinical exposure studies. A comprehensive review of such literature by Schlesinger and Cassee (2003) concluded that "[e]valuation of the toxicological database suggest that [sulfates] have little biological potency in normal humans or animals, or in the limited compromised animal models studied at environmentally relevant levels."[64] That being said, Schlesinger and Cassee temper their conclusion somewhat by raising the important point that the physicochemical characteristics of sulfates in these controlled studies differ somewhat from those to which humans are exposed. In addition, the controlled human exposure studies within this review do not (and generally could not) include the most sensitive subpopulations, who may be responsive at different levels or in different ways when compared with healthy populations. That being said, other recent review studies have made similar conclusions, indicating that the toxicological data linking sulfates to health effects have not found significant toxicity at ambient exposure levels (Schwarze et al., 2006; Grahame and Schlesinger, 2007).[65,66]

A portion of this inconsistency between the epidemiological and toxicological evidence may be attributable to the fact that exposures to ambient sulfate invariably occur in combination with a variety of other components, which are often not captured in toxicological studies. Beyond the usual complications of finding concordance between epidemiology and toxicology, this reflects the specific difficulty in trying to assign relative toxicity values to each individual component given that people are exposed to numerous components simultaneously. Hypothetically, if it were true that sulfates were not toxic when people were exposed to them in isolation, but that they enhanced the potency of metals that were ubiquitous in the atmosphere, reductions in sulfate concentrations would tend to lead to public health benefits, and this would need to be addressed within health benefits analysis.

5.4.1.2 Nitrate

Nitrate has not been as extensively studied as sulfate in terms of epidemiological or toxicological evidence. The limited time-series studies that have included nitrates in their analyses have found statistically significant results for all-cause and/or cardiovascular mortality (Fairley 2003; Ostro et al., 2007; Hoek, 2003).[67,68,69] A recent study of

---

[64] Schlesinger RB, and F. Cassee. 2003. Atmospheric Secondary Inorganic Particulate Matter: The Toxicological Perspective As A Basis For Health Effects Risk Assessment. Inhal Toxicol. Vol. 15(3):197-235.

[65] PE Schwarze, J Øvrevik, M La˚g, M Refsnes, P Nafstad, RB Hetland and E Dybing. 2006. Particulate Matter Properties And Health Effects: Consistency Of Epidemiological And Toxicological Studies.

[66] Grahame, T.J. and Schlesinger, R.B., 2007. Health Effects of Airborne Particulate Matter: Do We Know Enough to Consider Regulating Specific Particle Types or Sources. Inhalation Toxicology. Vol. 19(6): 457-481.

[67] Fairley, D. 2003. Mortality and air pollution for Santa Clara County, California, 1989–1996. In *Revised analyses of time-series studies of air pollution and health, Special report*, pp. 97–106. Boston, MA: Health Effects Institute.

cardiovascular mortality in southern California did find a significant effect of nitrate with a nearly identical C-R function as $PM_{2.5}$ as a whole, although interpretation is complicated by the high correlation between nitrate and $PM_{2.5}$ in California (Ostro et al., 2008).[70] A multi-city study focusing on hospital admissions found a weak positive association with cardiovascular hospital admissions and no association with respiratory hospital admissions (Bell et al., 2009).[71] Nitrate has not been included in large, long-term cohort studies.

An extensive review study examining toxicological data on the health effects of nitrate concluded that these studies have not found effects at ambient exposure levels (Schlesinger and Cassee, 2003).[72] However, the limited database for nitrate makes it difficult to make conclusions about its possible effects, and similar issues exist in interpreting toxicological evidence for nitrate as described for sulfate above.

5.4.1.3 EC/OC

There is limited epidemiological evidence supporting the development of C-R functions between elemental or organic carbon and mortality or morbidity. Cardiovascular mortality was found to be associated with EC and OC in California in Ostro et al. (2007) and with EC in Phoenix in Mar et al. (2000 & 2003).[73,74] EC and OC showed effects in a recent study of cardiovascular mortality in southern California that were slightly weaker than those of $PM_{2.5}$ as a whole (Ostro et al., 2008).[75] Coefficient of haze (CoH) was used as a proxy for EC in a study in Canada, which found a positive but statistically weak association between CoH and daily mortality (Burnett 2000 & 2003).[76] In a multi-city study, EC was associated with increased cardiovascular and respiratory hospital admissions, while OC was weakly associated with respiratory hospital admissions and not

[68] Ostro, B. et al., 2007. The Effects of Components of Fine Particulate Air Pollution on Mortality in California: Results from CALFINE. Environmental Health Perspectives. Vol. 115(1): 13-19.

[69] Hoek, G. 2003. Daily mortality and air pollution in The Netherlands. In: Revised analyses of time-series studies of air pollution and health. Special report. Boston, MA: Health Effects Institute; pp. 133-142.

[70] Ostro, B. et al., 2008. The Impact of Components of Fine Particulate Matter on Cardiovascular Mortality in Susceptible Subpopulations. Occup Environ Med. Published Online 16 April 2008.

[71] Bell, M.L. et al., 2009. *op. cit.*

[72] Schlesinger RB, and F. Cassee. 2003. *op. cit.*

[73] Ostro, B. et al., 2007. *op. cit.*

[74] Mar, T. F., Norris, G. A., Koenig, J. Q., and Larson, T. V. 2000. Associations between air pollution and mortality in Phoenix, 1995–1997. *Environ. Health Perspect.* 108:347–353. and Mar, T. F., Norris, G. A., Larson, T. V., Wilson, W. E., and Koenig, J. Q. 2003. Air pollution and cardiovascular mortality in Phoenix, 1995– 1997. In *Revised analyses of time-series studies of air pollution and health. Special report*, pp. 172–182. Boston: Health Effects Institute.

[75] Ostro, B. et al., 2008. *op. cit.*

[76] Burnett RT, Brook J, Dann T, Delocla C, Philips O, Cakmak S, Vincent R, Goldberg MS, Krewski D. 2000. Association between particulate- and gas-phase components of urban air pollution and daily mortality in eight Canadian cities. Inhal Toxicol. Vol. 12 Suppl 4:15-39. and Burnett, R. T.; Goldberg, M. S. 2003. Size-fractionated particulate mass and daily mortality in eight Canadian cities. In: Revised analyses of time-series studies of air pollution and health. Special report. Boston, MA: Health Effects Institute; pp. 85-90.

with cardiovascular admissions (Bell et al., 2009).[77] No association has been found in some panel studies looking at markers of cardiovascular health (e.g., Luttmann-Gibson et al., 2006; Sarnat et al, 2006), although other studies have demonstrated links with ST-segment depression (Gold et al., 2005) and myocardial repolarization (Henneberger et al., 2005).[78,79,80,81]

Thus, this literature does not demonstrate either the size or consistency necessary to determine quantitative relative toxicity values, but there is clearly no basis to exonerate EC or OC as a contributor to $PM_{2.5}$ health effects.

Studies examining the health effects of diesel exhaust from on-road and non-road vehicles may provide some additional insight into the health effects of EC and OC. The exhaust from new diesel vehicles (post-1990) has been found to be comprised of 75 percent (33- 90 percent) EC and 19 percent OC (7-49 percent) (USEPA, 2002).[82] In 2002, EPA published the "Health Assessment Document for Diesel Engine Exhaust," which was a comprehensive review of potential health effects from ambient exposure to exhaust from diesel engines (USEPA, 2002).[83] This document indicates that there is limited animal and human data showing short-term effects, such as neurophysiological symptoms (lightheadedness, nausea) and respiratory symptoms (cough, phlegm) as well as exacerbation of allergic responses and asthma-like symptoms.

Chronic effects of diesel exhaust have been studied in occupational cohort studies. Results of these studies show increased risk of respiratory symptoms (Gamble et al., 1987; Reger et al., 1982; Attfield et al., 1978) but do not indicate a consistent effect on pulmonary function (Battigelli et al., 1964; Ames et al., 1984; Attfield et al., 1982; Gamble et al., 1983).[84,85,86,87,88,89,90] However, these studies suffer from a number of

[77] Bell, M.L. et al., 2009 *op. cit.*

[78] Luttmann-Gibson H, H.H.Suh, B.A. Coull, D.W. Dockery, S.E. Sarnat, J. Schwartz, P.H. Stone, D.R. Gold. 2006. *op. cit.*

[79] Sarnat SE, H.H. Suh, B.A. Coull, J. Schwartz, P.H. Stone, D.R. Gold. 2006. *op. cit.*

[80] Gold DR, Litonjua AA, Zanobetti A, Coull BA, Schwartz J, MacCallum G, Verrier RL, Nearing BD, Canner MJ, Suh H, Stone PH. 2005. Air pollution and ST-segment depression in elderly subjects. Environ Health Perspect. Vol. 113(7):883-7.

[81] Henneberger A, Zareba W, Ibald-Mulli A, Rückerl R, Cyrys J, Couderc JP, Mykins B, Woelke G, Wichmann HE, Peters A. 2005. Repolarization changes induced by air pollution in ischemic heart disease patients. Environ Health Perspect. Vol.113(4):440-6.

[82] USEPA (2002). Health assessment document for diesel engine exhaust. Office of Research and Development, Washington, DC. EPA/600/8-90/057F.

[83] *Ibid.*

[84] Gamble J, Jones W, Minshall S. 1987. Epidemiological-environmental study of diesel bus garage workers: chronic effects of diesel exhaust on the respiratory system. Environ Res. Vol. 44(1):6-17.

[85] Reger R, Hancock J, Hankinson J, Hearl F, Merchant J. 1982. Coal miners exposed to diesel exhaust emissions. Ann Occup Hyg. Vol. 26(1-4):799-815.

[86] Attfield, MD. 1978. The effect of exposure to silica and diesel exhaust in underground metal and nonmetal miners. In: Industrial hygiene for mining and tunneling: proceedings of a topical symposium; November; Denver, CO. Kelley, WD, ed. Cincinnati, OH: The American Conference of Governmental Industrial Hygienists, Inc.; pp. 129-135.

methodological issues such as incomplete information on diesel exhaust exposure, the presence of confounding factors, and short duration and low intensity of exposures. Several occupational cohort studies have also found a relationship between diesel exhaust and lung cancer mortality (e.g., Saverin et al., 1999; Hansen et al., 1993; Gustavsson et al., 1990).[91,92,93] However, it is difficult to directly apply findings from occupational cohort studies to the general population, especially for outcomes such as chronic respiratory disease and given the goal to establish quantitative population C-R functions.

5.4.1.4 Metals

According to the HEI report, "Understanding the Health Effects of Components of the Particulate Matter Mix: Progress and Next Steps," metals are an important component of the PM mass of urban air in many settings (HEI, 2002).[94] Even though they generally constitute a small fraction of the total PM mass in most US settings, this component could be important to investigate given a small but growing base of epidemiological and toxicological evidence, and given that metals may be bound to other components comprising a greater portion of the total mass.

Limited epidemiological evidence exists examining the health effects of metals. Burnett et al. (2000) found that iron, nickel, and zinc were associated with increased mortality.[95] In fact, these metals were better predictors for mortality than total mass. In addition, Ostro et al. (2007) found positive statistically significant associations between daily mortality and iron, copper, vanadium, and zinc.[96] Franklin et al. (2008) determined that $PM_{2.5}$ mortality C-R functions were higher when the mass contained more aluminum, arsenic, and nickel.[97] Bell et al. (2009) found that communities with higher levels of

---

[87] Battigelli, MC; Mannella, RJ; Hatch, TF. 1964. Environmental and clinical investigation of workmen exposed to diesel exhaust in railroad engine houses. Ind Med Surg 33:121-124.

[88] Ames, RG; Reger, RB; Hall, DS. 1984. Chronic respiratory effects of exposure to diesel emissions in coal mines. Arch Environ Health 39:389-394.

[89] Attfield MD, Trabant GD, Wheeler RW. 1982. Exposure to diesel fumes and dust at six potash mines. Ann Occup Hyg. Vol. 26(1-4):817-31.

[90] Gamble, JF, Jones WG. 1983. Respiratory Effects of Diesel Exhaust in Salt Miners. Am Rev Respir Dis. 128:389-394.

[91] Saverin. R; Bräunlich, A; Dahman, D; et al. 1999. Diesel exhaust and lung cancer mortality in potash mining. Am J Ind Med 36:415-422.

[92] Hansen, ES. 1993. A follow-up study on the mortality of truck drivers. Am J Ind Med. 23:811-821.

[93] Gustavsson, P; Plato, N; Lidström, EB; et al. (1990) Lung cancer and exposure to diesel exhaust among bus garage workers. Scand J Work Environ Health 16:348-354.

[94] Health Effects Institute, 2002. Understanding the Health Effects of Components of the Particulate Matter Mix: Progress and Next Steps. Boston, MA.

[95] Burnett, R.T. et al., 2000. Association Between Particulate- and- Gas-Phase Components of Urban Air Pollution and Daily Mortality in Eight Canadian Cities. Inhalation Toxicology. Vol. 12(4): 15-39.

[96] Ostro, B. et al., 2007. *op. cit.*

[97] Franklin, M. et al., 2008. *op. cit.*

nickel and vanadium had elevated C-R functions for PM-related hospitalizations, a finding supported by others (Lippmann et al., 2006).[98,99]

Experimental studies on humans and animals suggest that metals could play an important role in both pulmonary inflammation and cardiovascular effects induced by PM (Schwarze et al, 2006).[100] For instance, *in vitro* and *in vivo* studies performed on PM filter extracts from Utah Valley in an area near a steel mill have documented pulmonary injury or inflammation (Ghio et al., 2004; Dye et al., 2001; Frampton et al., 1999).[101,102,103] These particles have been found to contain high levels of iron, copper, nickel, lead and zinc. In addition, several experimental studies suggest that metals could play a role in PM-induced cardiovascular effects. For example, copper, zinc and vanadium have been shown to induce a range of cardiovascular effects, such as vasoconstriction and vasodilation (Graff et al., 2004; Li et al., 2005; Bagate et al., 2004).[104,105,106]

According to Schwarze et al. (2006) in a review of the effects of metals, study approaches to date have not been able to pinpoint a specific metal or group of metals responsible for the health effects of PM; however, "vanadium, zinc, iron, copper and nickel stand out as potentially more important than other metals."[107]

5.4.1.5 Summary

There is a limited but growing literature addressing the health effects of various PM components, including (but not limited to) sulfate, nitrate, EC, OC, and metals. The conclusions are generally mixed for all individual components, with none either showing consistently greater effects than PM as a whole or demonstrating that they should not be assigned any toxicity. However, the epidemiological evidence base is clearly limited by

---

[98] Bell, M.L. et al., 2009. *op. cit.*

[99] Lippmann M, Ito K, Hwang JS, Maciejczyk P, Chen LC. 2006. Cardiovascular effects of Ni in ambient air. Environ Health Perspect 114:1662–1669.

[100] PE Schwarze et. al., *op. cit.*

[101] Ghio, A.J. 2004. Biological effects of Utah Valley ambient air particles in humans: a review. *Journal of Aerosol Medicine* 17(2): 157-164.

[102] Dye, J. A.; Lehmann, J. R.; McGee, J. K.; Winsett, D. W.; Ledbetter, A. D.; Everitt, J. I.; Ghio, A. J.; Costa, D. L. 2001. Acute pulmonary toxicity of particulate matter filter extracts in rats: coherence with epidemiological studies in Utah Valley residents. Environ. Health Perspect. 109(suppl. 3): 395-403.

[103] Frampton, M. W.; Ghio, A. J.; Samet, J. M.; Carson, J. L.; Carter, J. D.; Devlin, R. B. 1999. Effects of aqueous extracts of PM_{10} filters from the Utah Valley on human airway epithelial cells. Am. J. Physiol. 277: L960-L967.

[104] Graff DW, Cascio WE, Brackhan JA, Devlin RB. 2004. Metal particulate matter components affect gene expression and beat frequency of neonatal rat ventricular myocytes. Environ Health Perspect. Vol. 112(7):792-8.

[105] Li Z, Carter JD, Dailey LA, Huang YC. 2005. Pollutant particles produce vasoconstriction and enhance MAPK signaling via angiotensin type I receptor. Environ Health Perspect. Vol.113(8):1009-14.

[106] Bagate K, Meiring JJ, Gerlofs-Nijland ME, Vincent R, Cassee FR, and Borm PJ. 2004. Vascular effects of ambient particulate matter instillation in spontaneous hypertensive rats. Toxicology and applied pharmacology Vol. 197(1):29-39.

[107] PE Schwarze et. al., *op. cit.*

the high correlations among many PM components (and between those components and PM as a whole), and it is difficult to corroborate this evidence toxicologically given the fact that human exposure to single particle components is not a realistic scenario. More generally, for this evidence base to be applicable to a differential toxicity analysis, it would need to be able to provide quantitative C-R functions for all of the key components, derived in a manner so that the total reflected the observed effects of $PM_{2.5}$ and so that the estimates reflected possible interactions among components. The evidence base cannot currently support this sort of assessment.

5.4.2 SOURCE-ORIENTED EVALUATIONS

In light of the high correlations among various particle components, often owing to common sources, a smaller number of studies have used factor analyses and other techniques to determine latent source contributions that can be related with health outcomes (Laden et al, 2000; Mar et al., 2000). [108,109] These studies typically relate daily concentrations of PM components and gaseous co-pollutants to underlying source types (e.g., motor vehicle emissions, soil, etc.), using weighted linear combinations of associated individual variables. Although the results differ somewhat across studies, coal and oil combustion, vegetation burning, and motor vehicle emissions tend to be positively associated with mortality, whereas crustal particles tend to have a lesser association with mortality.

This approach is appealing in many respects, as EPA is evaluating the benefits of control strategies targeting specific sources, and these sorts of analyses can provide insight about which sources are most strongly associated with health outcomes. However, from a benefits analysis perspective, these evaluations have a number of limitations, and are unlikely to yield the evidence necessary for a quantitative differential toxicity analysis.

For example, emissions controls and technological changes may lead to changes in relative concentrations of components over time, complicating the application of a factor-specific C-R function to prospective analyses. For example, the study by Laden et al. (2000) used monitoring data from 1979-1988, at which point lead still served as a reasonable target element for a motor vehicle factor. [110] This term would not be directly applicable to the 812 prospective analysis, whose study period post-dates the phase-out of lead in gasoline. With the numerous regulations that have been implemented or promulgated over the years, it is unlikely that a “source” characterized at a given point in time would be directly applicable to a future scenario.

More generally, it is impractical to link the results of these studies with the outputs obtained from a dispersion model, a necessary condition for application in health benefits analysis. For example, if a study predicted a coal-related PM factor loading heavily on

[108] Laden, F.; Neas, L. M.; Dockery, D. W.; Schwartz, J. 2000. Association of fine particulate matter from different sources with daily mortality in six U.S. cities. Environ. Health Perspect. 108: 941-947.

[109] Mar, T. F.; Norris, G. A.; Koenig, J. Q.; Larson, T. V. 2000. *op. cit.*

[110] Laden, F.; Neas, L. M.; Dockery, D. W.; Schwartz, J. 2000. *op. cit.*

sulfur and selenium, characterizing those emissions and modeling those concentrations can prove challenging. Relatedly, the relative contribution of components from a source would vary by distance, complicating the application of a source-specific signature at a given receptor, which would not be the same as the composition of emissions or the signature at a different distance from a source.

Also, any individual PM component may come from a variety of sources. Correlated concentrations and multiple sources of specific components complicate the identification of individual effects of various $PM_{2.5}$ components on a national scale (Bell et al, 2007).[111] Thus, while these studies have tremendous value in interpreting the epidemiological literature, they are not likely to be practical for health benefits analysis.

Despite improved monitoring and a growing database of speciated PM data, significant challenges and uncertainties remain when trying to address the issue of differential toxicity within benefits analysis. For a number of reasons, even with the growth of epidemiological evidence utilizing speciated PM data, it may remain challenging to provide quantitative C-R functions for individual PM components. The reasons for this include:

- Components may interact; effects may not be a linear combination of exposures and may depend on particular combinations of components. Epidemiological studies have not modeled nonlinear combinations, and it would be challenging to capture synergistic or antagonistic effects of particle combinations in light of the numerous covarying exposures, the size of the anticipated signal, and the lack of biological understanding of the potential interactions.
- It will remain difficult for the foreseeable future to assess the concordance of epidemiological and toxicological results. Even if toxicological studies or controlled human exposure studies could determine that specific particle components (e.g., nitrate) do not produce adverse effects at ambient concentrations, it would be difficult for such studies to capture phenomena where particles may be heterogeneous combinations of multiple components, and where some particles may act as carriers for some chemical or biological toxic agent. The increasing use of concentrated ambient particles (CAPs) provides a realistic ambient aerosol for toxicological studies, but has difficulty in separating out the effects of individual components in a way that would be useful for benefits analysis.
- Data remain limited on the spatial and temporal variability of $PM_{2.5}$ components, though as noted above, progress is being made here based on the growing speciation network (Bell et al. 2007).[112]
- Even when epidemiological evidence is derived from the speciation network, the C-R functions for different components will vary by site, and it is difficult to

[111] Bell, M.L. et al., 2007. *op. cit.*

[112] *Ibid.*

determine the extent to which this is related to potential unique aspects of PM composition in each location or to random variability. More generally, in multi-city comparisons using between-city differences to evaluate differential toxicity, it is difficult to isolate the exclusive effect of differential toxicity, given other important effect modifiers and confounders that exist in site-specific studies (e.g., concentration-exposure relationships modified by air conditioning prevalence, vulnerability distributions).

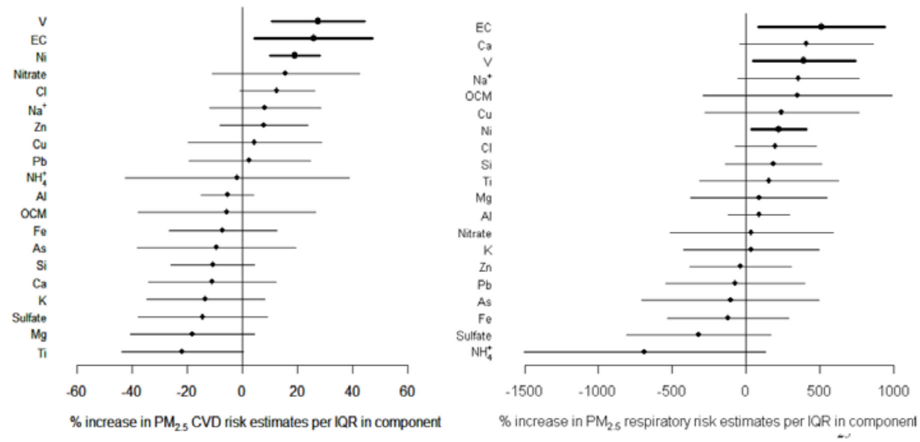
- Control strategies would remove a combination of components that may not be the same as the combinations observed in prior epidemiological or toxicological studies. Understanding the effects of sulfate particles in the past may not be the same as understanding the benefits of removing sulfate particles from the current atmosphere.

These are daunting challenges that are not likely to be resolved soon. However, the literature on the health effects of individual components or component mixtures is growing rapidly, and one could consider how the current epidemiological evidence base could be used to construct sensitivity analyses that remain notional but are logically consistent, as well as how an "ideal" epidemiological evidence base could be used in the future to provide an empirical basis for differential toxicity sensitivity analyses.

In general, these sorts of analyses are likely to rely on time-series estimates for mortality and morbidity, given a sufficient number of studies and sites to formally and quantitatively explore differential toxicity. There are relatively fewer cohort studies, and as described above, only a handful of PM component estimates from those studies. In addition, the differential toxicity analyses would most likely be derived from meta-analyses of single-city epidemiological studies, or from multi-city investigations using Bayesian hierarchical models or related methods, depending on the nature of the available evidence. The latter approach might be preferable, since individual epidemiological studies may report only a subset of components, potentially biasing pooled estimates, but meta-analytic approaches can provide valuable insight in the absence of large multi-city studies.

In either case, this would allow for pooled estimates to be developed for a number of individual components, as done in studies such as Bell et al. (2009). [113] Figure 3 from this paper is replicated below, as it helps to illustrate the potential and pitfalls of such investigations.

[113] Bell, M.L. et al., 2009. *op. cit.*



In principle, functions such as these could be used to directly estimate C-R functions for individual PM components. However, this does not account for the covariance among components. For example, ammonium would generally be found bound to either sulfate or nitrate, and many particles covary due to common sources or atmospheric processes. Moreover, if C-R functions were developed per μg/m^3 (as would be necessary for a differential toxicity assessment), the values would vary enormously across components, mostly within confidence intervals that are quite large. Focusing on only the high-mass components would make this problem somewhat less intractable, but the uncertainties would remain large in any relative toxicity assessment.

For example, just focusing on EC and V for cardiovascular hospital admissions (which are both statistically significant, reducing uncertainties in the relative toxicity comparison), Bell et al. report a 25.8% increase per interquartile range increase of EC (95% CI: 4.4%, 47.2%), versus a 27.5% increase per interquartile range increase of V (95% CI: 10.6%, 44.4%). Given interquartile ranges of 0.245 μg/m^3 for EC and 0.001 μg/m^3 for V, a literal interpretation of these functions implies potency for V that is over 200 times that of EC using the central estimates. If these confidence intervals were uncorrelated, a simple simulation method analysis indicates that the 95% confidence interval for the ratio of V potency to EC potency is (-380, 1,900). If the confidence intervals were correlated at the level of correlation between EC and V (0.33), the 95% confidence interval for the ratio would be (-13, 1,400). Even assuming a correlation of 0.90, the 95% confidence interval would be approximately (100, 730).

Clearly, these specific results are dependent on a single study and its values. However, it has been documented previously that comparing ratios of two uncertain distributions will have an extremely large confidence interval, to the extent that estimates of relative potency using central estimates would be highly misleading (Finkel, 1995).[114] Thus, even "gold standard" epidemiological studies with component data would likely yield relative toxicity values that are quite uncertain. These uncertainties could be reduced if the original studies directly estimated relative potency values, rather than having them interpreted after the fact from published studies.

5.6 CONCLUSIONS

We conclude that the current evidentiary base from the epidemiological and toxicological literatures is insufficient to support a meaningful policy-relevant analysis of the implications of estimating avoided mortality using C-R functions based on individual PM components instead of $PM_{2.5}$ mass. The epidemiological evidence collected to date provides limited and inconsistent evidence on the relative potency of the key PM components that are both a significant contributor to, and co-vary with, total PM mass. These data gaps would limit the informativeness of even the most straightforward (linear) combination of potencies. Furthermore, the available epidemiological and toxicological evidence suggests that we are dealing with a much more complex system of particle interactions that could be improperly characterized by a simple linear combination approach. Characterization of any of these more complicated "what if" potency scenarios would require more support from the epidemiological and toxicological literatures and more detailed air quality modeling data on metals and other PM components.

The current data gaps are significant. Advancements that would be needed to undertake a meaningful and interpretable policy relevant treatment of uncertainty in the potency of individual PM components include:

Epidemiology. Improved epidemiology is key to development of the population C-R functions. The ideal study of differential toxicity would be a multi-city epidemiological investigation with sufficient information about particle composition and related exposures (varying over both time and location), good characterization of vulnerable populations, and good specificity in health outcomes (with characterization of multiple such outcomes). Useful studies would need to be able to provide quantitative concentration-response functions for all of the key components, both those that co-vary with PM mass and others (e.g., metals) that have been implicated in existing studies, derived in a manner so that the total reflected the observed effects of $PM_{2.5}$ and so that the estimates reflected possible interactions and correlations among components. For reasons discussed above, studies that provide estimates of potency of individual components from single pollutant models are less useful due to extensive correlations among particles and the wide uncertainty bounds associated with developing potency ratios across such results.

Multi-city epidemiological investigations or meta-analyses of numerous individual-city studies could also provide insights about differential toxicity by investigating compositional/correlational factors explaining between-city variability. Approaches could include meta-regression techniques or forms of cluster analysis, which have been

[114] Finkel, A.M. 1995. Towards Less Misleading Comparisons of Uncertain Risks: The Example of Aflatoxin and Alar. Environmental Health Perspectives, Vol. 103(4), 376-385.

successful in related analyses. However, as discussed above, such analyses would be challenged by the fact that numerous characteristics associated with exposures or outcomes vary across cities and regions, including weather, personal exposure patterns (driven by air conditioning and other factors), and vulnerability characteristics. Moreover, the relative consistency of estimates across settings in the present literature would indicate the likely challenges in such an assessment. However, such assessments would likely represent the only means for developing quantitative estimates of relative toxicity and should be explored.

Source-oriented epidemiologic studies. While these studies are intrinsically limited by the fact that source contributions vary spatially and by the challenges in linking source-oriented epidemiologic studies with outputs from atmospheric models used in health benefits analysis, there may be limited settings in which such studies would be fruitful. Specifically, in the near-roadway environment, epidemiological studies that characterize the contribution from various traffic sources could ultimately be applied in the narrow context of evaluating the health benefits for near-field populations associated with primary pollutant control strategies. Factor-analytic approaches would need to be developed jointly with atmospheric model refinements to ensure that the relevant pollutants could be characterized and that the correlation structures implicit in the source-oriented factors exist within the designated receptor domain.

Toxicology. While not likely to provide the basis for the C-R function, sound toxicology is needed to provide corroboration of biological plausibility and mechanisms of disease and to contribute to our understanding of uncertainty in potency estimates. In theory, sound toxicological evidence could help to determine the subset of constituents plausibly associated with targeted health outcomes, allowing for other constituents to be dismissed as non-causal and therefore excluded from epidemiological investigation. However, developing such toxicological evidence would be challenging. Future studies should not focus on the toxic effects of exposures to individual components; rather they should focus on mixtures, doses, and outcomes (e.g., cardiovascular disease and mortality) that would be relevant to the exposures experienced in epidemiological studies. Ideally these would be conducted on animal populations with disease models that capture particularly vulnerable individuals. Toxicological studies that are conducted in parallel with multi-city epidemiological studies and that evaluate exposures to PM samples collected from at least a subset of the cities being studied could help provide useful corroborating toxicological evidence that may identify key elements of more potent PM mixtures.

Air Quality Modeling. As attention shifts towards the role of components such as metals that contribute less mass to overall $PM_{2.5}$, or to components that may be prominent indicators of key PM sources, air quality models need to adapt to model the transport and transformation of these components to produce concentration estimates that could be coupled with more traditionally modeled PM components in a benefits analysis.

CHAPTER 6 | PARTICULATE MATTER/MORTALITY CESSATION LAG

6.1 SELECTION OF PM/MORTALITY LAG STRUCTURES

Based in part on prior advice from the Advisory Council on Clean Air Compliance Analysis (hereafter, the Council), EPA typically assumes that there is a time lag between reductions in particulate matter (PM) exposures in a population and the full realization of reductions in premature mortality. Within the context of benefits analyses, this term is often referred to as "cessation lag." The existence of such a lag is important for the valuation of reductions in premature mortality because economic theory suggests that dollar-based representations of health effect incidence changes occurring in the future should be discounted. We applied a five percent discount rate to calculate the net present value of a stream of future benefits that begins in each target year of the analysis (i.e., 2000, 2010, or 2020).

The Project Team explored the effect on monetized benefits of model uncertainty related to the cessation lag for PM-related reductions in mortality risk. We selected two alternative cessation lag structures to include in our analysis in addition to the default lag employed in the primary 812 benefits assessment (the 20-year distributed lag). The default lag and one of the alternative lags (five-year distributed lag) have been used by EPA in previous benefits analyses and are step functions. The third is a new alternative lag structure, which we developed based on an exponential decay function (hereafter, the "smooth function"). We describe below the default cessation lag structure as well as the two alternative structures and the rationale for including them in the analysis.

6.1.1 DEFAULT TWENTY-YEAR DISTRIBUTED LAG

The 20-year distributed lag, which is applied in the integrated report, assumes that 30 percent of the total mortality reductions occur in the first year, 50 percent are distributed evenly among years two through five, and the remaining 20 percent are distributed evenly among years six through 20. In 2002, the National Research Council (NRC) of the National Academy of Sciences evaluated EPA's use of the five-year distributed lag model in previous air pollution benefits analysis and found little justification for the five-year time course of exposure and outcome. In response to the NRC report, the EPA identified three alternative options in the analytic blueprint for the Second Section 812 Prospective Study:[115] (1) the currently employed five-year distributed lag, (2) an alternative based on a range of lag structures from zero to 20-30 years, and (3) construction of a 3-parameter Weibull distribution configured to match (undefined) expected low, most likely, and

[115] US EPA (2003). Benefits and Costs of the Clean Air Act 1990-2020: Revised Analytical Plan for EPA's Second Prospective Analysis. Prepared by Industrial Economics, Inc for the Office of Policy Analysis and Review.

expected high values. The EPA requested comment from the Council's Health Effects Subcommittee (HES) on these three approaches.

In a March 2004 advisory report, the Council HES provided an in-depth assessment of the cessation lag issue and the three approaches put forth by the EPA.[116] This report echoed the earlier reports by the HES predecessor, the Health and Ecological Effects Subcommittee (HEES), and NRC in noting that the empirical evidence is lacking to inform the choice of lag distribution directly and further, that there is little evidence supporting a five-year cessation lag structure. The Council HES urged the EPA "to begin to move from the relatively arbitrary assumptions of the five-year lag structure to an approach based on some plausible models of the disease process involved," and goes on to state that lacking direct empirical evidence, "new insights regarding the shape of the cessation lag can only come from improved understanding of the mechanism of the exposure-response relationship." Taking this advice into consideration and working with the Office of Management and Budget (OMB) on the non-road diesel rule, EPA identified an alternative lag structure that assumes 20 percent of the mortality reductions occur in the first year, 50 percent are distributed evenly among years two through five, and the remaining 30 percent are distributed evenly among years six through 20.

A December 6, 2004 letter from the Council reviewed the 20-year lag proposed by the EPA and states that "this proposal is broadly consistent with our recommendations, and preferable to the five-year distributed lag used earlier," but suggests a slight modification.[117] Based on the air pollution evidence, which is generally suggestive of greater impacts in the first year, and some recent evidence from intervention studies, which suggest that substantial benefits might occur in the first year, the Council recommended that the EPA use a 20-year lag structure, where 30 percent of the mortality reductions occur in the first year, 50 percent are distributed evenly among years two through five, and the remaining 20 percent are distributed evenly among years six through 20. This is the 20-year lag structure applied as the basis for the primary benefits estimate.

6.1.2 FIVE-YEAR DISTRIBUTED LAG

The first alternative lag structure we employed as one of our alternatives is a five-year distributed lag structure, which was used in *The Benefits and Costs of the Clean Air Act, 1990 to 2010* and in other rulemaking analyses, such as the Heavy Duty Diesel Regulatory Impact Analysis (RIA) and the Tier II Motor Vehicle Emissions Standards

[116] Science Advisory Board (2004). Advisory on Plans for Health Effects Analysis in the Analytical Plan for EPA's Second Prospective Analysis—Benefits and Costs of the Clean Air Act, 1990-2020: Advisory by the Health Effects Subcommittee of the Advisory Council on Clean Air Compliance Analysis. EPA-SAB-COUNCIL-ADV-04-002.

[117] Science Advisory Board (2004). *Advisory Council on Clean Air Compliance Analysis Response to Agency Request on Cessation Lag*. Letter from the Health Effects Subcommittee to the U.S. Environmental Protection Agency Administrator, December.

RIA.[118] The five-year distributed lag assumes that 25 percent of the mortality reductions occur in the first year, an additional 25 percent occur in the second year, and the remaining 50 percent are distributed evenly among years three through five. This five-year distributed lag structure was adopted by EPA in 1999 after review of various structures by the HEES. EPA asked the HEES to consider three lag options: (1) a zero lag, the current practice at the time, (2) a five-year distributed lag, which had been used in an illustrative analysis in the proposed Tier II RIA and (3) a 15-year lag proposed by OMB that assumed all incidence changes occur in the 15th year following the change in exposure. The HEES concluded that the five-year distributed lag was preferable to the zero and 15-year options, both of which they considered implausible. The HEES also indicated that available data on smoking cessation generally supported the five-year distributed lag (although it did not provide any specific citations). The health effects of PM exposure are similar to other long-term inhalation exposures, such as cigarette smoking. Therefore, HEES considered information from the smoking cessation literature relevant to the PM/mortality cessation lag question.

6.1.3 SMOOTH FUNCTION LAG

In its 2004 letter recommending a 20-year lag structure, the Council urged EPA to review and keep abreast of the emerging literature in this area, including information from the smoking cessation literature; provide the best available justification for the lag structure used; and strongly consider conducting sensitivity analyses of other possible lag structures. Specifically, the Council indicated that EPA should consider using smoothed distributions. In response to these suggestions, the Project Team performed a literature review that included studies published since 2004. Using the PubMed search engine (www.pubmed.gov), we searched for articles related to PM/mortality cessation lag as well as recently published papers on smoking cessation and environmental tobacco smoke (ETS) exposure cessation.

Through our search of literature exploring the PM/mortality cessation lag, we identified a 2005 paper by Roosli et al.[119] The authors of this study developed a smooth function lag that assumes that mortality risks decrease exponentially after exposure termination. This assumption is based on the fact that an exponential model is often observed in biological systems. We chose to base our third lag structure on the approach employed by this paper because it allowed us to use data from existing PM/mortality cohort studies as well as intervention studies as described further below. In addition, its use is consistent with

[118] United States Environmental Protection Agency (1999). *The Benefits and Costs of the Clean Air Act 1990 to 2010*. EPA Report to Congress.

United States Environmental Protection Agency (2000). *Regulatory Impact Analysis: Heavy-Duty Engine and Vehicle Standards and Highway Diesel Fuel Sulfur Control Requirements*. Office of Air and Radiation. EPA420-R-00-026.

United States Environmental Protection Agency (1999). *Regulatory Impact Analysis - Control of Air Pollution from New Motor Vehicles: Tier 2 Motor Vehicle Emissions Standards and Gasoline Sulfur Control Requirements*. Office of Air and Radiation. EPA420-R-99-023.

[119] Roosli, M., N. Kunzli, et al. (2005). Years of life lost attributable to air pollution in Switzerland: dynamic exposure-response model. *International Journal of Epidemiology* 34(5): 1029-35.

the Council's advice to explore smoothed distributions. Details of the lag structure are provided below.

6.1.3.1 Description of the Roosli Model

Roosli et al. developed a dynamic model that estimates the course of mortality after a sudden reduction of air pollution exposure. The model assumes an exponential decrease of risk of death after exposure termination at time t_0, of the form $risk = \exp^{-kt}$, where k is the time constant and t is the time after t_0. The relative risk from air pollution (RR) at a given time (t) can be calculated from the excess relative risk (ERR) attributable to air pollution from PM cohort studies ($ERR = RR - R_0$), as follows:

$$RR(t) = ERR \cdot \exp^{-kt} + R_0 \,, \tag{1}$$

where R_0 is the baseline relative risk in the absence of air pollution ($R_0 = 1$). After cessation of exposure, mortality will start to decline and approach the baseline level. The change in mortality (ΔM), in units of percent-years, can be derived from Equation (1) as follows:

$$\Delta M = ERR \cdot t - \int_0^t ERR \cdot \exp^{-kt} \, dt \tag{2}$$

Estimates of ΔM can be obtained from PM intervention studies. Integrating Equation (2) gives:

$$\Delta M = ERR \cdot t - \frac{ERR}{k} + \frac{ERR}{k} \exp^{-kt} \,. \tag{3}$$

6.1.3.2 Application of the Roosli Model

We first identified possible PM cohort studies to use as the source of *ERR* values in Equation 3. We included the follow-up analyses of the two major existing cohorts, the Six Cities Cohort (Laden et al., 2006) and the American Cancer Society (ACS) Cohort (Pope et al., 2002).[120,121] We standardized the published RR estimates from these two studies to represent a 10 µg/m^3 increase in PM_{10}.[122] In addition, we used the primary estimate of the PM/mortality concentration-response (C-R) function used in the integrated report, which is based on a Weibull distribution of C-R coefficients with a mean of 1.06 percent decrease in annual all-cause mortality per 1 µg/m^3 and an interquartile range bracketed approximately by the Pope et al. 2002 ACS estimate (0.55 percent) on the low

[120] Pope, CA III, et al. (2002). Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. *JAMA* 287: 1132-1141.

[121] Laden, F., et al. (2006). Reduction in fine particulate air pollution and mortality – Extended follow-up of the Harvard Six Cities Study. *Am J Respir Crit Care Med* 173: 667-672.

[122] In order to convert the published RRs from $PM_{2.5}$ to PM_{10}, we used the same factor used in the Roosli et al. analysis of 1.33.

end and the Six Cities Laden et al., 2006 extended follow-up estimate (1.5 percent) at the high end.

We then collected information from PM intervention studies to develop estimates of ΔM for Equation 3. In particular, we relied on data on the time course of the change in mortality from two PM intervention studies to determine ΔM. Clancy et al. (2002) analyzed the change in mortality in Dublin following the ban of coal sales (hereafter, the "Dublin Coal Ban" study).[123] This study found a 1.6 percent decrease in mortality per 10 $\mu g/m^3$ PM_{10} over a six-year period, resulting in a ΔM of 0.1 percent-years (0.016×6). A study by Pope et al. (1992) examined the change in mortality resulting from the closure of a steel mill in the Utah Valley (hereafter, the "Utah Valley" study).[124] This study reported a 2.1 percent decrease in mortality per 10 $\mu g/m^3$ PM_{10} over a 13-month period (corresponding to a ΔM of 0.02 percent-years (0.021×1.083)).[125]

We iteratively solved Equation (3), to calculate values for the time constant, *k*, using the ΔM values from the two intervention studies along with the *ERR* values from the two cohort studies.

Finally, to address the Council's suggestion to incorporate data from the smoking cessation literature, we also used information from a study that developed a dynamic model that took into account the decrease in risk after the termination of an exposure to air pollution using smoking cessation as a proxy for air pollution exposure (Leksell and Rabl, 2001).[126,127,128] This study relied on a time constant of 9.55 years, which was based on studies examining the body's ability to repair the damage after an individual stops smoking. This was derived by calculating a weighted average of a time constant of 1.5 years for acute myocardial infarction and stroke (Lightwood and Glantz, 1997; weighted with 0.3) and a time constant of 13 years for total mortality (Doll et al., 1994; weighted with 0.7).[129,130]

---

[123] Clancy, L., P. Goodman, et al. (2002). Effect of air-pollution control on death rates in Dublin, Ireland: an intervention study. *Lancet* 360(9341): 1210-4.

[124] Pope, C.A., J. Schwartz, M.R. Ransom. (1992). Daily mortality and PM10 pollution in Utah Valley. *Archives of Environmental Health* 47:211-17.

[125] Note that we also considered data from the Six Cities study update (Laden et al., 2006), which found a 27 percent decrease in mortality risk per 10 $\mu g/m^3$-reduction of $PM_{2.5}$ in Period 2 (1990-1998) when controlling for exposure in Period 1 (1974-1989). However, the value of k resulting from this estimate is very large and therefore is equivalent to applying no lag. Therefore, we did not include this in our sensitivity analysis.

[126] Leksell, I. And Rabl, A. (2001). Air pollution and mortality: Quantification and valuation of years of life lost. *Risk Analysis* 21(5): 843-857.

[127] An external reviewer, Lauraine Chestnut of Stratus Consulting, Inc., also recommended deriving a k value from Leksell and Rabl (2001). Her comments and recommendations are summarized in a memorandum dated March 31, 2009 (Chestnut, 2009).

[128] We were unable to identify any articles providing information on the length of the lag between the cessation of environmental tobacco smoke (ETS) exposure and mortality. We identified several additional studies examining the change in health risks after cessation of smoking, however, few specifically estimated all-cause mortality effects.

[129] Lightwood, J.M. and Glantz, S.A. (1997). Short-term economic and health benefits of smoking cessation: Myocardial infarction and stroke. *Circulation* 96: 1089-1096.

We then used the derived values of k to calculate the decrease in risk after exposure termination using the following equation: $risk = \exp^{-kt}$. Exhibit 6-1 below provides the k values we used in our uncertainty analysis as well as the studies underlying them.

EXHIBIT 6-1. VALUES OF THE TIME CONSTANT (k) USED IN THE EXPONENTIAL DECAY PM/MORTALITY CESSATION LAG FUNCTION

VALUE OF K	COHORT STUDY	INTERVENTION STUDY
0.05	Six Cities[1]	Dublin Coal Ban[2]
0.08	Primary Estimate	Dublin Coal Ban
0.10	Smoking Cessation Literature[3]	
0.15	ACS[4]	Dublin Coal Ban
0.37	Six Cities	Utah Valley[5]
0.57	Primary Estimate	Utah Valley
1.24	ACS	Utah Valley

[1] Laden, F., et al. (2006). Reduction in fine particulate air pollution and mortality - Extended follow-up of the Harvard Six Cities Study. *Am J Respir Crit Care Med* 173: 667-672.
[2] Clancy, L., P. Goodman, et al. (2002). Effect of air-pollution control on death rates in Dublin, Ireland: an intervention study. *Lancet* 360(9341): 1210-4.
[3] Leksell, I. And Rabl, A. (2001). Air pollution and mortality: Quantification and valuation of years of life lost. *Risk Analysis* 21(5): 843-857.
[4] Pope, CA III, et al. (2002). Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. *JAMA* 287: 1132-1141.
[5] Pope, C.A., J. Schwartz, M.R. Ransom. (1992). Daily mortality and PM10 pollution in Utah Valley. *Archives of Environmental Health* 47:211-17.

Exhibit 6-2 below displays the relationship between the ERR and ΔM terms in Equation 2 when deriving the k values. Combining the ERRs from the cohort studies with the Dublin Coal Ban study (shown in the top three graphs) results in lower k values (i.e., a more gradual decline in risk) than when the Utah Valley intervention study is used. This is because the Utah Valley study found a larger total decrease in mortality (2.1 percent versus 1.6 percent) within a shorter timeframe (13 months versus 6 years). Therefore, the evidence from this study supports a cessation lag structure where deaths are accrued more quickly after the PM change. In addition, for a given intervention study (and therefore ΔM), smaller ERRs result in higher k values. For instance, the k derived from the combination of the Utah Valley intervention study and the Laden cohort study is 0.37, compared to a k of 1.24 from the Pope cohort study. This is because in order to achieve the percent reduction in mortality found in the intervention study within the given

[130] Doll, R., et al. (1994). Mortality in relation to smoking: 40 years' observations on British doctors. *British Medical Journal* 309: 901-911.

timeframe, *t*, a smaller *ERR* requires a more rapid decline to occur in the *ERR(t)* function, and hence a larger decay constant.

6.2 CALCULATION OF MORTALITY INCIDENCE AND VALUATION USING LAG STRUCTURES

BenMAP currently does not have the capability to apply a cessation lag to the mortality incidence results data. Therefore, the Project Team constructed a spreadsheet that would apply alternate cessation lag models to the BenMAP results as a post-processing step.

The spreadsheet uses the estimates of avoided deaths from BenMAP generated from the use of the Community Multi-scale Air Quality model (CMAQ) exposure model for each target year, along with an estimate of the default Value of a Statistical Life (VSL) of $7.4 million in 1990 (in 2006$), and a five percent discount rate, to calculate the net present economic value of the modeled stream of monetized benefits under each lag assumption.[131]

6.3 EFFECT OF ALTERNATIVE CESSATION LAG STRUCTURES

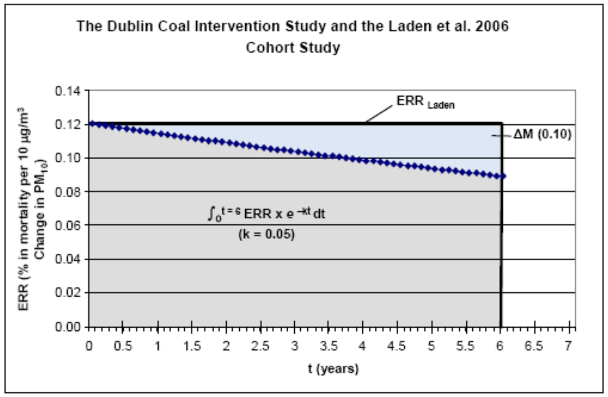
The exponential decay function that we employed as a new alternative lag structure relies on time constant values derived from combining information from a particular PM cohort and intervention study pair. Therefore, use of this smooth function implies that selecting an alternate C-R function will affect not only the total avoided mortality (as described in Chapter 4) but also the way in which that avoided mortality accrues over time following a change in exposure. We first present the effects of applying the two step functions and the exponential functions derived from the primary C-R function to the mortality incidence results generated with the primary C-R function. We also compare the results of applying the exponential decay function lag based on the smoking literature to the primary C-R function. We next present the relative benefits resulting from applying the two step functions and the exponential decay functions derived from the Pope and Laden studies to the mortality incidence results generated from Pope and Laden C-R functions.

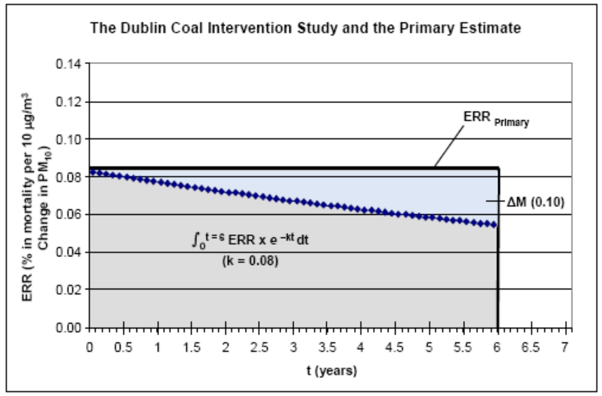
6.3.1 CESSATION LAG RESULTS BASED ON THE PRIMARY C-R FUNCTION ESTIMATE

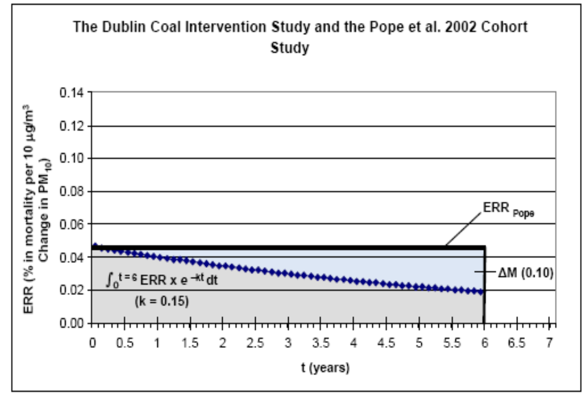
Exhibits 6-3 and 6-4 show the difference in the timing of avoided deaths due to Clean Air Act Amendment (CAAA)-related $PM_{2.5}$ changes in 2020 when applying the various cessation lag structures to the primary mortality incidence results. Exhibit 6-3 shows the number of deaths that would occur in each year and Exhibit 6-4 compares the cumulative number of avoided deaths over time. Exhibit 6-5 displays the mean valuation results using the default 20-year distributed lag and the percent change in valuation that occurs as a result of employing each of the alternative cessation lag structures. We present below a summary of the key impacts of varying the cessation lag model on the primary estimates of mortality reductions due to CAAA programs:

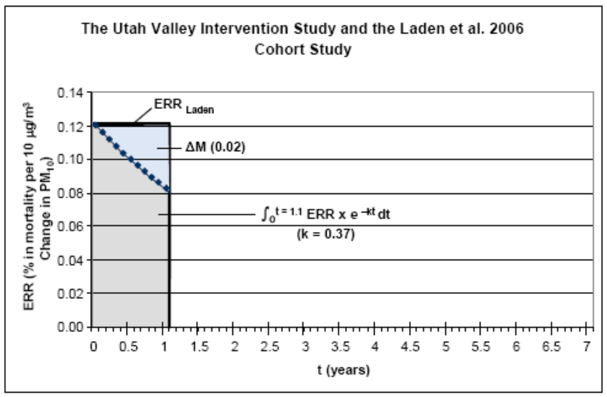
[131] This approach is equivalent to discounting future VSLs from the years in which mortality reductions are expected to occur and multiplying each discounted VSL times avoided deaths in that year. The approach does not discount future avoided deaths.

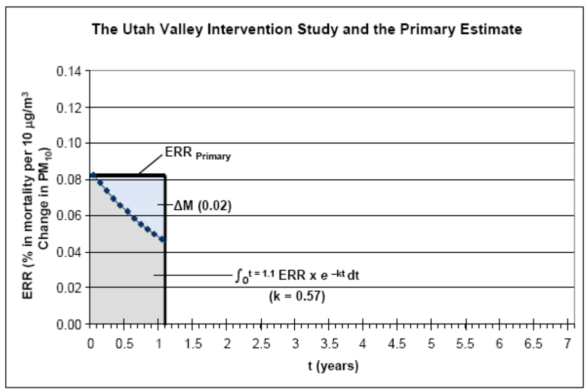
EXHIBIT 6-2. RELATIONSHIP BETWEEN THE CHANGE IN MORTALITY OBSERVATION STUDIES AND THE EXCESS RELATIVE RISKS FROM PM COHORT STUDIES WHEN DERIVING AN EXPONENTIAL DECAY TIME CONSTANT

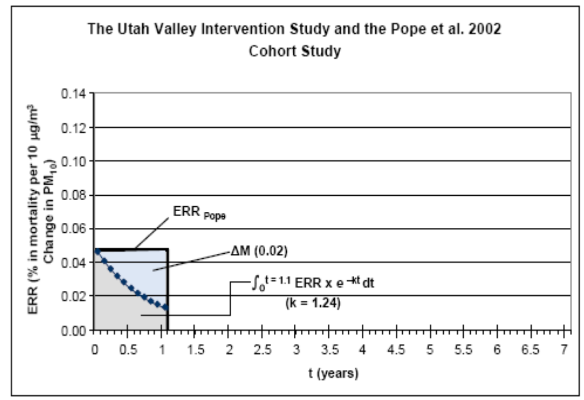












- The five-year distributed lag valuation results are roughly nine percent higher than the 20-year distributed lag assumption. This is due to the fact that the avoided deaths in the 20-year lag assumption are spread over a longer time period and the corresponding VSLs are more heavily discounted, while under the five-year lag assumption, 50 percent of deaths occur within the first two years and all deaths occur within five years.
- The results based on the smooth function lag structure vary depending on the time constant selected. When relying on the k value derived from the primary C-R function and the Dublin Coal Ban study (k = 0.08), the economic value decreases 23 percent from the default. This reflects the fact that the avoided deaths are spread over a longer period of time after the exposure change. The benefits that accrue far into the future are assigned less economic value because the VSL is more heavily discounted. Applying the k value derived from primary C-R function and the Utah Valley study (k = 0.57) results in valuation estimates that are 10 percent higher than the default lag assumption. Use of the k value derived from the smoking cessation literature (k = 0.10) results in a monetary benefits estimate that is 18 percent lower than the 20-year distributed lag.
- Assuming no lag, and therefore no discounting of VSL, results in an increase in benefits of approximately 16 percent above the default, 20-year distributed lag.

EXHIBIT 6-3. ALTERNATE CESSATION LAGS - ANNUAL DEATHS (PRIMARY ESTIMATE)

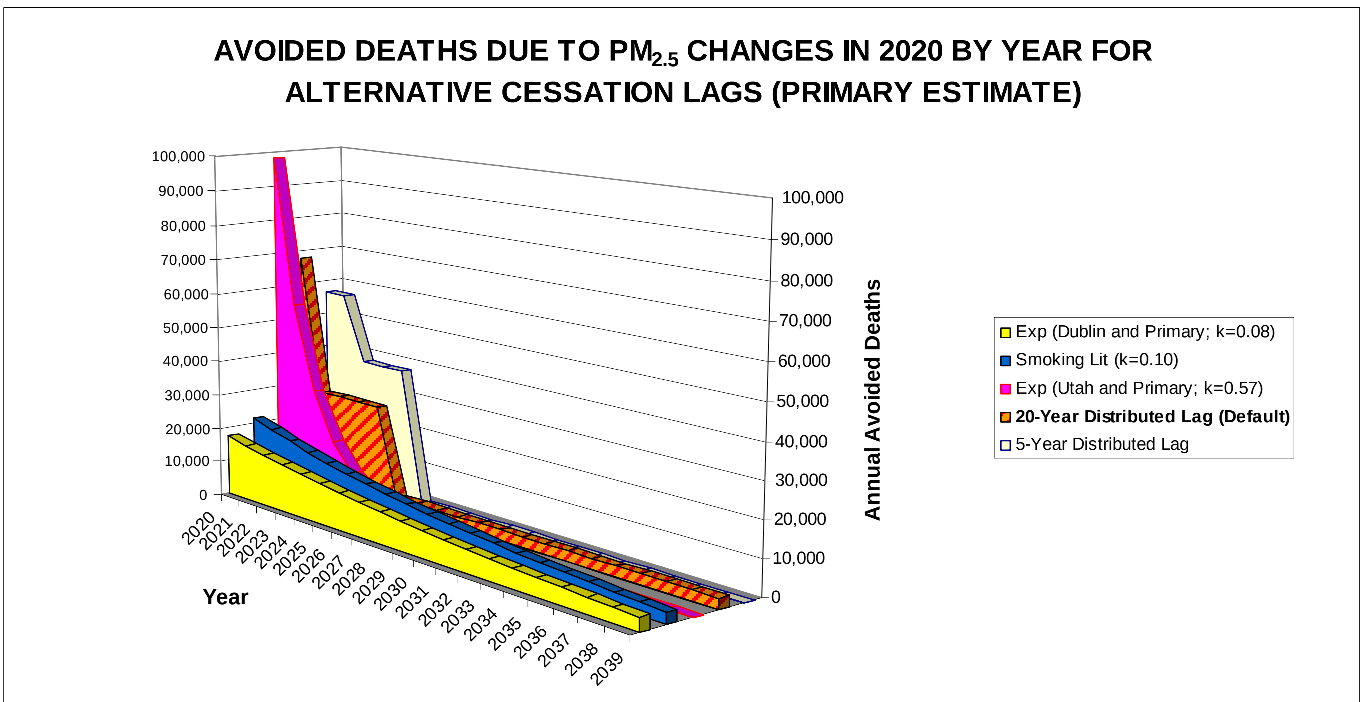


EXHIBIT 6-4. ALTERNATE CESSATION LAGS – CUMULATIVE DEATHS (PRIMARY ESTIMATE)

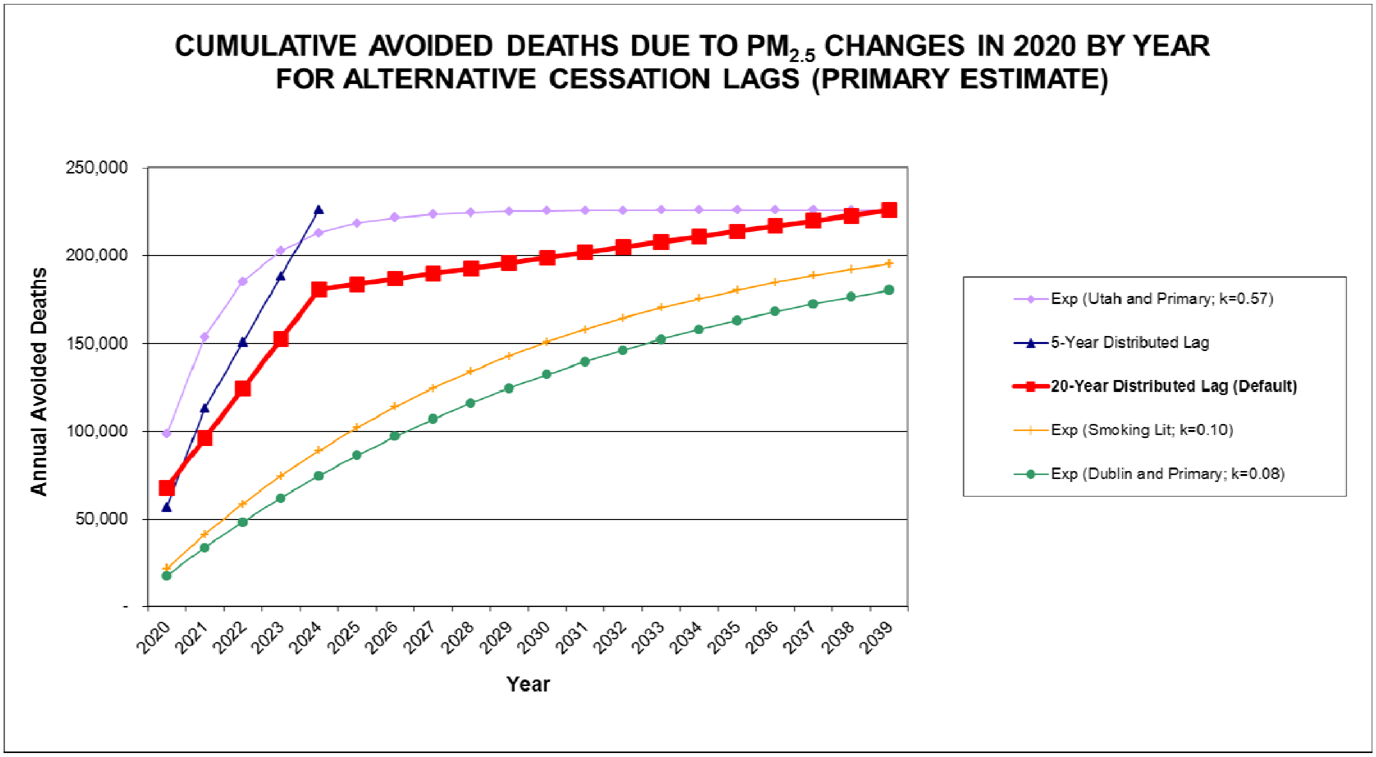


EXHIBIT 6-5. VALUATION RESULTS FOR THE PRIMARY C-R FUNCTION ESTIMATE AND THE EFFECT OF USING ALTERNATIVE LAG STRUCTURES

MORTALITY CESSATION LAG	
Primary Estimate with 20-Year Distributed Lag – 2000	**710,000**
Primary Estimate with 20-Year Distributed Lag – 2010	**1,200,000**
Primary Estimate with 20-Year Distributed Lag – 2020	**1,700,000**
	Percent Change from the Primary Estimate with Default Lag*
Primary Estimate with 5-Year Distributed Lag	9%
Primary Estimate with Smooth Function, k = 0.08 (Dublin Intervention Study)	-23%
Primary Estimate with Smooth Function, k = 0.10 (Smoking cessation)	-18%
Primary Estimate with Smooth Function, k = 0.57 (Utah Valley Intervention Study)	10%
No Lag, No Discounting	16%
* All values in the table represent the percent change from the mean primary estimate. Percent change estimates do not vary by target year.	

6.3.2 CESSATION LAG RESULTS BASED ON POPE ET AL., 2002

Exhibits 6-6 and 6-7 show the difference in the timing of avoided deaths due to CAAA-related $PM_{2.5}$ changes in 2020 when applying the various cessation lag structures to the Pope mortality incidence results. Exhibit 6-6 shows the number of deaths that would occur in each year and Exhibit 6-7 compares the cumulative number of avoided deaths over time. Exhibit 6-8 displays the percent change in valuation results from the primary estimate (i.e., the primary C-R function estimate with the 20-year distributed lag) as a result of employing each of the alternative lag structures to the Pope incidence results. We present below a summary of the key results of varying both the C-R function employed and the cessation lag model on the primary estimates of avoided mortality due to CAAA programs:

- The use of the Pope et al. incidence estimates along with the default 20-year distributed lag result in valuation estimates that are 43 percent lower than the primary estimate. Since we are only varying the incidence estimate and not the lag structure, this difference is solely due to the different magnitudes of the two C-R functions.

- Applying the 5-year distributed lag to the Pope incidence results in a benefits estimate that is 42 percent lower than the primary estimate. In this case, the reduction in avoided mortality due to the lower Pope C-R coefficient dominates the effect of shortening the lag period and increasing the percentage of benefits accrued in early years.

- The results based on the smooth function lag structure vary depending on the time constant selected. When relying on the k value derived from Pope and the Dublin Coal Ban study (k = 0.15), the economic value decreases 52 percent from the default. This reflects the fact that the avoided deaths are spread over a longer period of time after the exposure change, but again the bulk of the impact comes from changing the C-R function. Applying the k value derived from Pope and the Utah Valley study (k = 1.24) results in valuation estimates that are similar to assuming no lag, since 71 percent of avoided mortality occurs within the first year. These results are 37 percent lower than the default lag assumption, again illustrating that the results are less sensitive to the choice of cessation lag than they are to the choice of C-R coefficient.

EXHIBIT 6-6. ALTERNATE CESSATION LAGS - ANNUAL DEATHS (POPE ET AL., 2002)

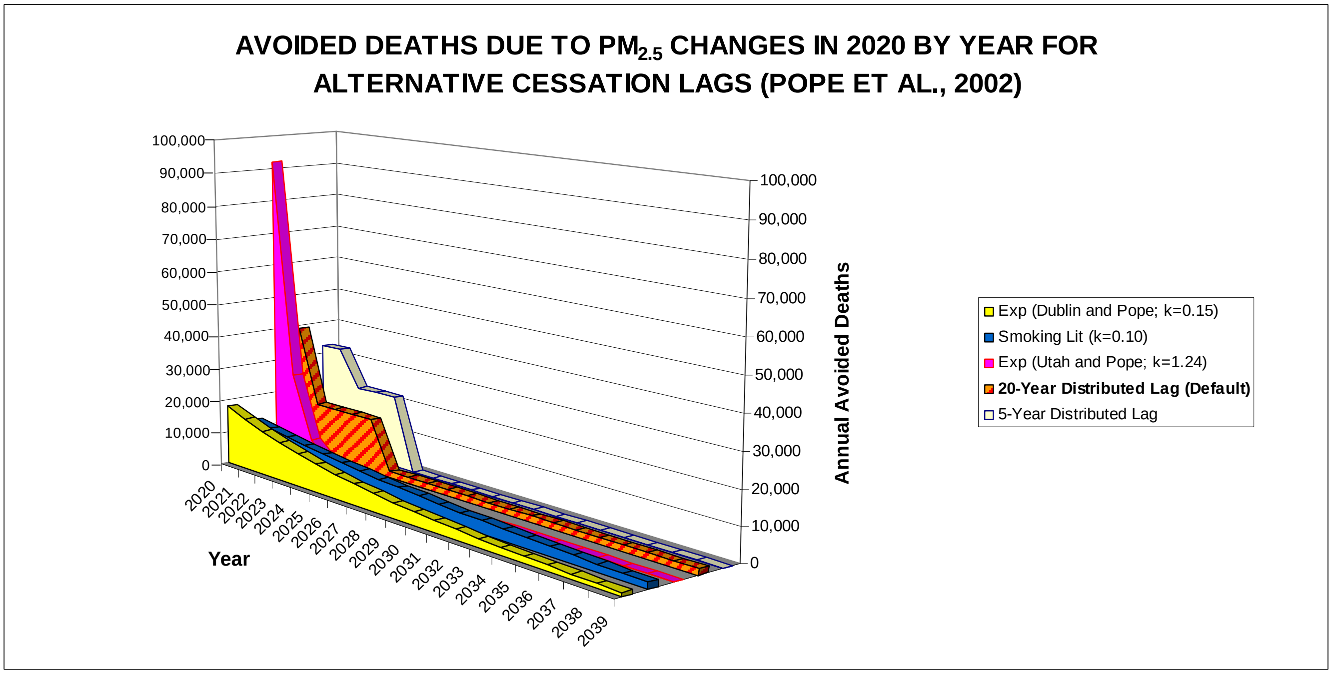


EXHIBIT 6-7. ALTERNATE CESSATION LAGS - CUMULATIVE DEATHS (POPE ET AL., 2002)

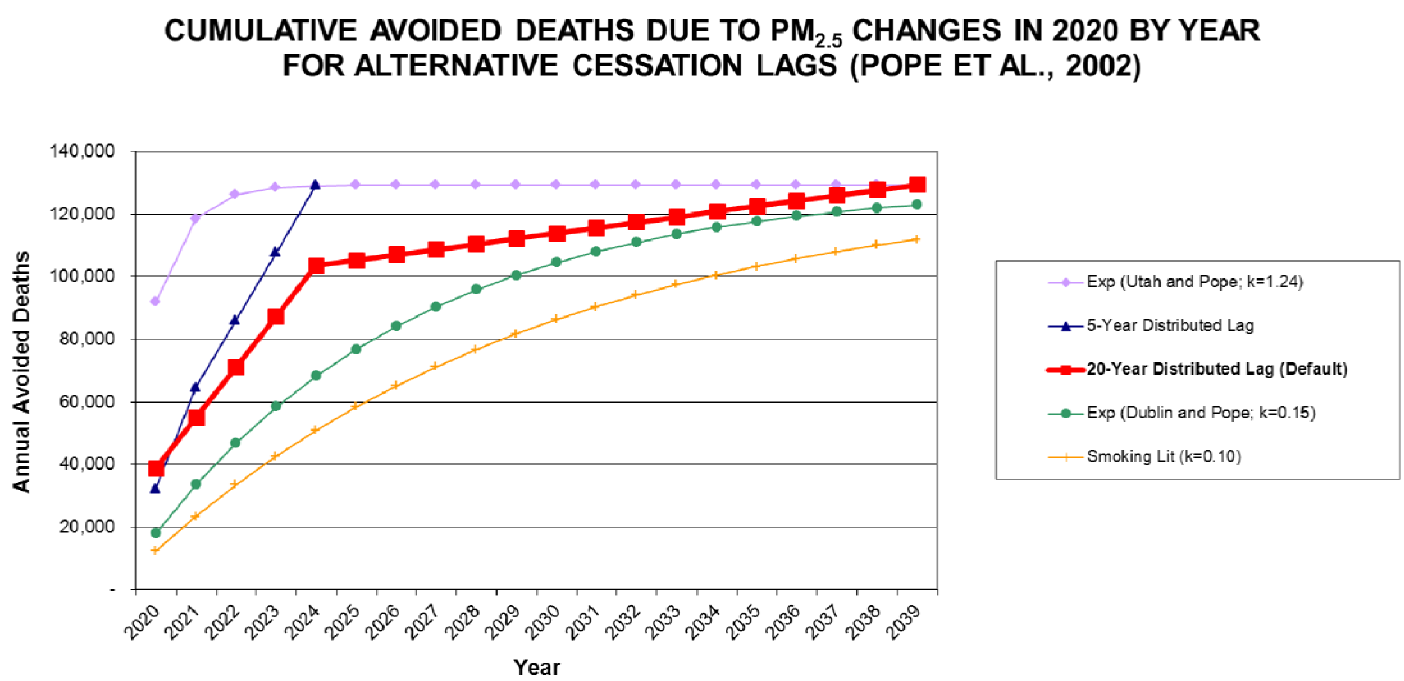


EXHIBIT 6-8. RELATIVE VALUATION RESULTS USING ALTERNATIVE LAG STRUCTURES – POPE ET AL., 2002

MORTALITY CESSATION LAG	PERCENT CHANGE FROM PRIMARY ESTIMATE WITH DEFAULT LAG*
Pope et al. 2002 with 20-Year Distributed Lag	-43%
Pope et al. 2002 with 5-Year Distributed Lag	-42%
Pope et al. 2002 with Smooth Function, k = 0.15 (Dublin Intervention Study)	-52%
Pope et al. 2002 with Smooth Function, k = 1.24 (Utah Valley Intervention Study)	-37%

* All values in the table represent the percent change from the mean primary estimate. Percent change estimates do not vary by target year.

6.3.3 CESSATION LAG RESULTS BASED ON LADEN ET AL., 2006

Exhibits 6-9 and 6-10 show the difference in the timing of avoided deaths due to CAAA-related $PM_{2.5}$ changes in 2020 when applying the various cessation lag structures to the Laden mortality incidence results. Exhibit 6-9 shows the number of deaths that would occur in each year and Exhibit 6-10 compares the cumulative number of avoided deaths over time. Exhibit 6-11 displays the percent change in valuation results from the primary estimate (i.e., the primary C-R function estimate with the 20-year distributed lag) as a result of employing each of the alternative lag structures to the Laden incidence results. We present below a summary of the key results of varying both the C-R function employed and the cessation lag model on the primary estimates of avoided mortality due to CAAA programs:

- The use of the Laden incidence results with the 20-year distributed lag result in benefits estimates that are 37 percent higher than the primary estimate, due to the larger RR reported by Laden et al. as compared with the primary C-R function.
- Applying the 5-year distributed lag to the Laden incidence estimates results in benefits that are 47 percent higher than the primary estimate. This is due to both the difference in the magnitude of the C-R functions as well as the fact that the avoided deaths in the 20-year lag assumption are spread over a longer time period and the corresponding VSLs are more heavily discounted, while under the five-year lag assumption, 50 percent of deaths occur within the first two years and all deaths occur within five years. In this case, the increase in avoided mortality due to the higher Laden C-R coefficient dominates the effect of shortening the lag period and increasing the percentage of benefits accrued in early years.
- As with the primary C-R function estimate and the Pope results, the results based on the smooth function lag structure vary depending on the intervention study selected. When relying on the k value derived from Laden and the Dublin Coal Ban study (k = 0.05), the economic value is 12 percent lower the primary estimate. Application of this time constant spreads the avoided deaths over a very long time period, causing the economic value to be heavily reduced due to discounting. In this case, the application of the alternative lag dominates over the different C-R function, reducing the benefits estimate below the primary estimate. Applying the k value derived from Laden and the Utah Valley study (k = 0.37) results in valuation estimates that are 47 percent higher than the default value, a similar estimate to the five-year lag application.

EXHIBIT 6-9. ALTERNATE CESSATION LAGS - ANNUAL DEATHS (LADEN ET AL., 2006)

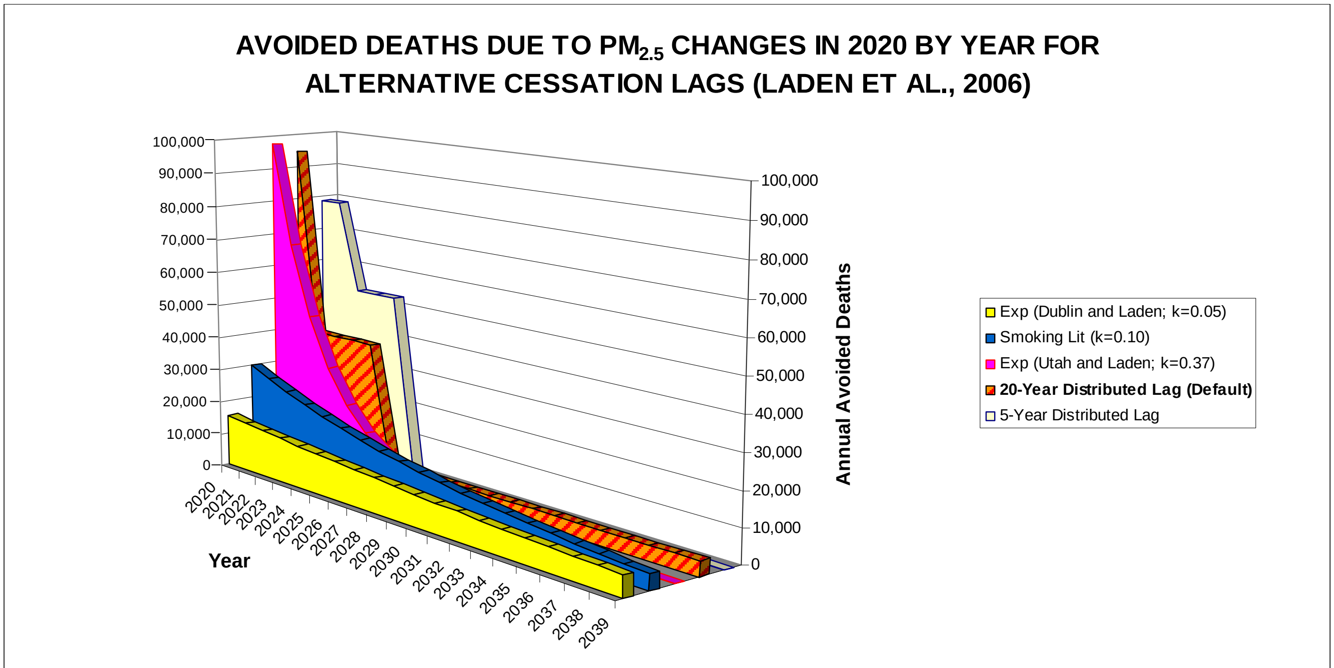


EXHIBIT 6-10. ALTERNATE CESSATION LAGS - CUMULATIVE DEATHS (LADEN ET AL., 2006)

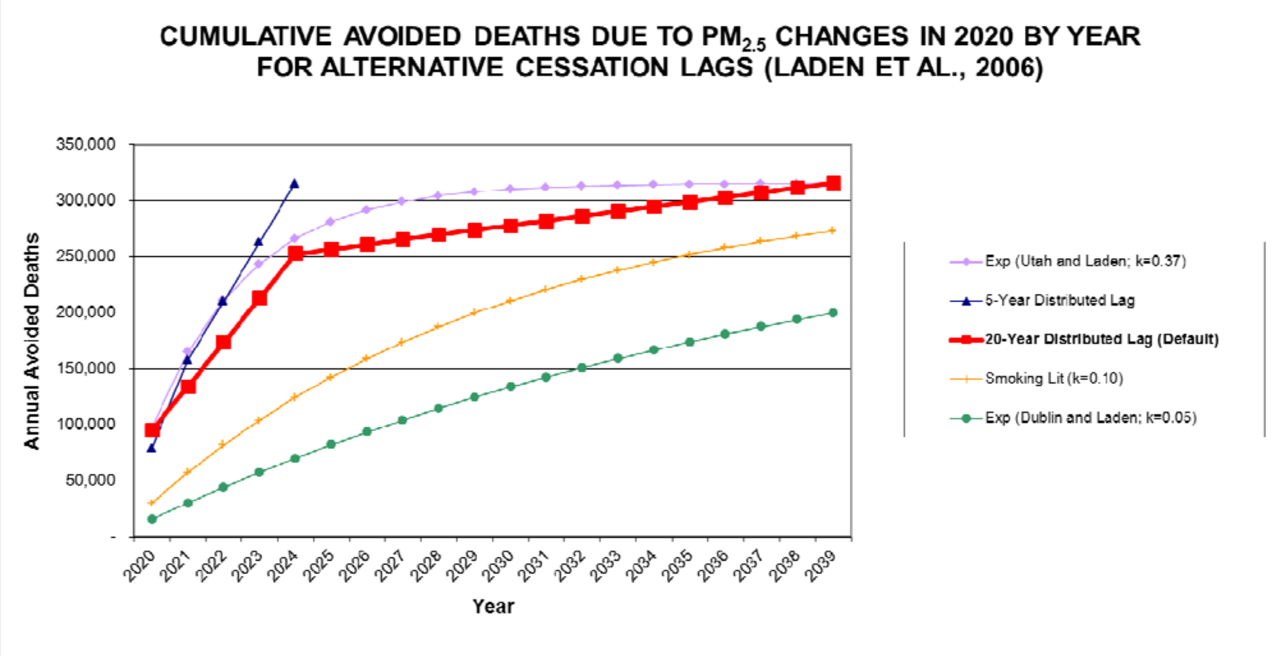


EXHIBIT 6-11. MEAN VALUATION RESULTS USING ALTERNATIVE LAG STRUCTURES – LADEN ET AL., 2006

MORTALITY CESSATION LAG	PERCENT CHANGE FROM PRIMARY ESTIMATE WITH DEFAULT LAG*
Laden et al. 2006 with 20-Year Distributed Lag	38%
Laden et al. 2006 with 5-Year Distributed Lag	50%
Laden et al. 2006 with Smooth Function, k = 0.05 (Dublin Intervention Study)	-13%
Laden et al. 2006 with Smooth Function, k = 0.37 (Utah Valley Intervention Study)	45%

* All values in the table represent the percent change from the mean primary estimate. Percent change estimates do not vary by target year.

CHAPTER 7 | DYNAMIC POPULATION MODELING

7.1 INTRODUCTION

EPA's standard approach to estimating the mortality effects of air pollutant exposure involves application of the BenMAP tool. Although BenMAP incorporates growth in population over time, the fundamental approach is based on a static population model, which does not differ across scenarios or update over time.

In this chapter, we describe the Project Team's deployment of a supplementary approach to $PM_{2.5}$-related premature mortality and population effects using a dynamic population model. The dynamic population simulation model was developed with EPA funding and is described briefly in this chapter and in detail elsewhere.[132]

7.2 DESCRIPTION OF THE POPULATION SIMULATION MODEL

The dynamic population simulation model we applied is a spreadsheet-based approach that is based on principles established in prior research.[133] The model was designed to track the effect of alternative assumptions about the mortality effects of $PM_{2.5}$ in the U.S. population over time. The tool incorporates detailed life table data for historical years, by age, gender, and cause of death, obtained from the Census Bureau and the Centers for Disease Control and Prevention (CDC). It also incorporates Census mortality and population projections for future years, again by age and gender, using the projected death and birth rates that underlie the Census Bureau's published population projections.

This model allows users to:

- Simulate population in the U.S. by single year of age and gender for years between 1990 and 2050 under alternative assumptions about the degree of hazard posed by air pollution relative to baseline historical and projected Census mortality rates;
- Estimate changes in life years relative to baseline Census mortality rates;
- Apply air pollution hazards differentially by cause of death; and

[132] Industrial Economics, Inc. (2006). *Population Simulation Model for Air Pollution Hazards, Version 1.1 - User Manual and Documentation*. Prepared for the Office of Policy Analysis and Review, U.S. Environmental Protection Agency, September.

[133] See, for example, B.G. Miller and J.F. Hurley, "Life table methods for quantitative impact assessments in chronic mortality," *Journal of Epidemiology and Community Health*, 57:200–206, 2003, and Röösli, M., N. Künzli, C. Braun-Fahrländer, and M. Egger. 2005. Years of life lost attributable to air pollution in Switzerland: Dynamic exposure-response model. *International Journal of Epidemiology*. 34(5):1029-1035.

- Analyze the effect of alternative cessation lag structures on the timing of total mortality and on total life years in the U.S. population, based on differential application by cause of death or other specifications of cessation lag.

The model provides users the capability to manually enter a user-specified beta coefficient or use the epidemiologic data pre-loaded into the model, and accounts for the impact of overlapping cessation lags for each change to determine the net impact on mortality hazard in each year. In addition, users can specify the trajectory of PM changes over time as either a step function or through linear interpolation between target years. Users can also incorporate a $PM_{2.5}$ threshold concentration, explore the impacts of varying susceptibility to air pollution by age; and, using the Crystal Ball™ spreadsheet overlay software, can run a version of the model using probabilistic inputs for the beta coefficient and threshold concentration to model the effect of uncertainty in these parameters on the outcome measures.

All calculations and results in the model are conducted at the national level, using average changes in national average PM levels or population-weighted exposure. The model can be used to estimate changes in mortality risk for years between 1990 and 2050. The temporal range provides a "run-up" period using the more highly resolved by-cause mortality data available for historical years, and allows for testing of hypotheses on a retrospective and prospective basis.

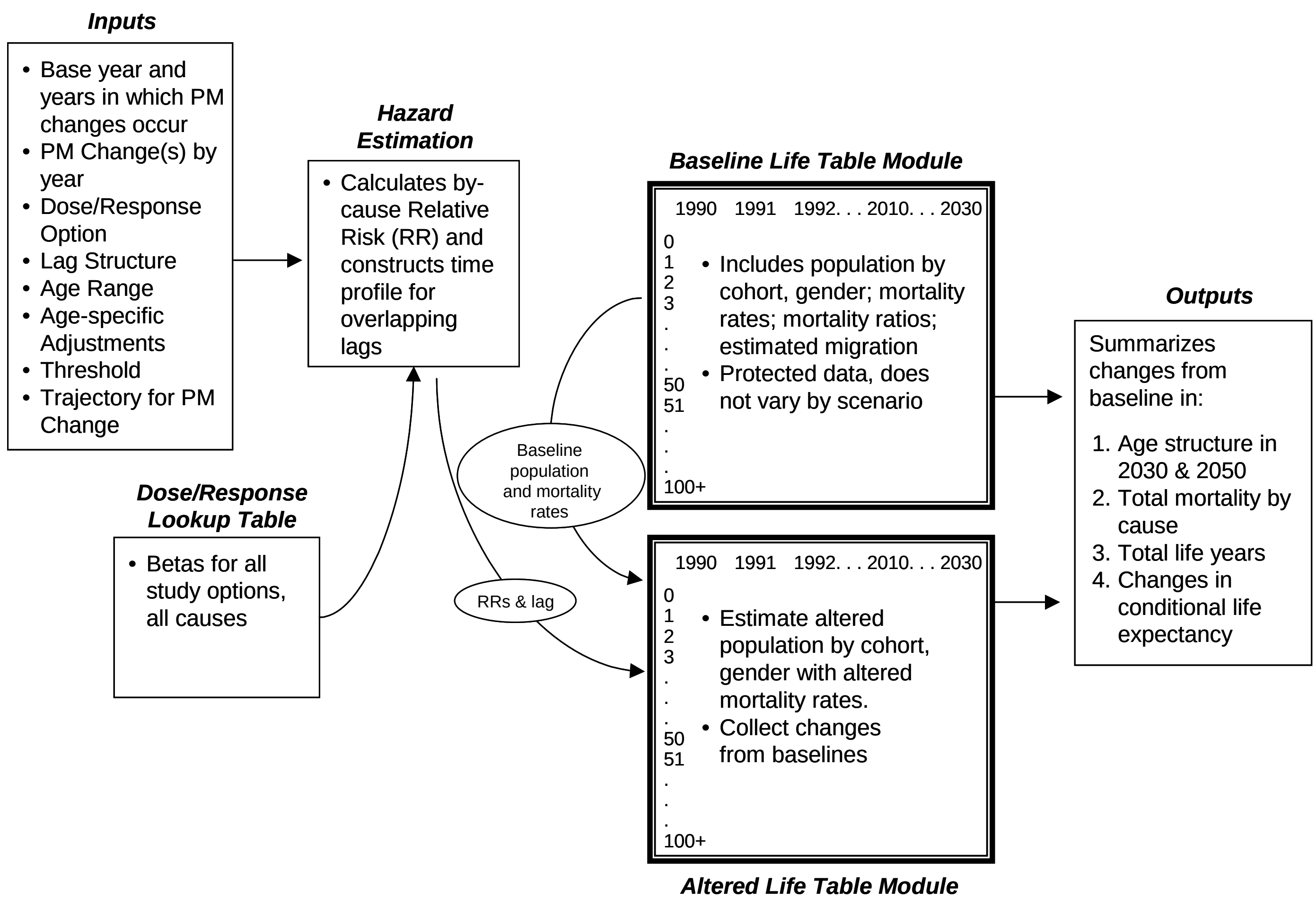
The model consists of five linked components, as illustrated in Exhibit 7-1: Inputs, Hazard Estimation, Baseline Life Table, Regulatory Life Table, and Outputs. The five components include seven spreadsheets in total, one each for Inputs, Hazard Estimation, and Outputs, and two each (one for males and one for females) for the Baseline and Regulatory Life Table Modules.

7.3 APPLICATION OF THE POPULATION SIMULATION MODEL

The Project Team used the spreadsheet-based dynamic population simulation model described above to explore the effect of CAAA-related PM changes on the population. The population simulation model at this time can only estimate changes in mortality due to a single change in $PM_{2.5}$ nationwide. However, the CMAQ output consists of $PM_{2.5}$ concentrations at the CMAQ 36 km grid cell level. Therefore, we calculated national population-weighted average $PM_{2.5}$ concentrations for each target year and scenario (*with*- and *without-CAAA*) using the CMAQ data for the core scenarios and population data at the CMAQ 36 km grid cell level generated using EPA's PopGrid program.[134]

[134] This program relies on population projections from Woods and Poole.

EXHIBIT 7-1. CONCEPTUAL FRAMEWORK FOR UPDATED POPULATION SIMULATION MODEL



We then input the incremental difference in $PM_{2.5}$ concentration between the baseline and control scenario for the first target year (2000) and then the incremental difference in $PM_{2.5}$ concentration from the previous target year to the current target year for 2010 and 2020. We input incremental changes rather than absolute changes in PM because the population simulation model assumes that each concentration change is permanent. Therefore, each subsequent change results in an impact on the mortality rate equivalent to the cumulative total effect of air pollution changes up to that point in time. We also assumed that the PM changes would occur gradually over time. For instance, we took the total CMAQ-derived PM change in 2000 and spread it evenly between 1990 and 2000, assuming a linear trajectory. In addition, we applied the default 20-year distributed lag to each PM change. We chose to apply this incremental, linear change in PM because it is a standard option in the population simulation model and it is a reasonably close approximation of how CAAA-related PM changes would occur over time and how the baseline mortality rate would be affected in the control scenario.

The results presented below are based on application of the Pope et al. (2002) PM C-R function and EPA's current standard 20-year distributed cessation lag. Other C-R function and cessation lag assumptions are possible in the model, but were not explored for this draft. No threshold was applied.

7.4 RESULTS

Exhibits 7-2 through 7-4 below provide the standard output from the population simulation model for the runs configured as outlined above, in terms of changes in number of deaths per year, life years gained, and changes in period conditional life expectancy. Exhibit 7-2 provides the estimated change in number of deaths per year by age cohort for the simulation period 1990 through 2050. The estimates presented are for a single year (they are not cumulative for the prior or next five-year period) based on differences in population tables by cohort and year between two life tables – one that simulates population with the CAAA, which is our baseline scenario, and one that simulates population without the CAAA, a scenario with higher PM concentrations and, as a consequence higher mortality rates in cohorts where the PM C-R function applies (adults age 30 and over). The estimates represent differences from the baseline, *with-CAAA* scenario, so most of the estimates are negative, indicating higher mortality in the *without-CAAA* scenario. The simulation could have been run in the opposite direction, but the Project Team believes that the baseline population data from Census is meant to illustrate mortality rates consistent with the factual, *with-CAAA* scenario – and because this is a dynamic model, the results are not reflexive.

As illustrated in the table, changes in the life tables begin in 1995 and the difference in total deaths continues to grow through 2020. Not surprisingly, initially all cohorts experience fewer deaths in the cleaner, *with-CAAA* scenario, but because more individuals are alive to enter older, higher baseline mortality cohorts, the oldest three cohorts in particular begin to quickly experience more deaths in the *with-CAAA* scenario, and the number of additional deaths grows in these cohorts over time. This phenomenon is only seen in the oldest cohorts – in all other cohorts, there are fewer deaths in the *with-CAAA* scenario. Note that the CAAA is not the cause of more deaths – it is that the life-extending qualities of less air pollution exposure yield higher numbers of individuals surviving to cohorts with high non-pollution mortality rates. Examination of the life tables shows that more individuals survive in all cohorts.

The number of deaths estimate, then, is fundamentally different from that estimated by BenMAP. While BenMAP estimates the number of deaths that will eventually be avoided as a result of a single improvement in air pollutant exposure for a given year, the population simulation approach incorporates a series of dynamic processes, including multiple annual exposure changes, overlapping lag periods, and dynamic effects of changes in air pollutant mortality rates that operate each year in concert with age-specific mortality rates. Individuals are "passed" from year to year and each year experience a new level of mortality risk, depending on age-specific non-air-pollutant risks and an exposure dependent air pollutant risk. Deaths tabulated in Exhibit 7-2 are therefore total number of deaths from all causes, a fundamentally different measure that cannot be compared to the estimate from BenMAP, but which supplements that estimate.

Exhibit 7-3 illustrates a second output from the population simulation model, estimated life years gained by age cohort and year of the simulation. These estimates effectively compare the number of individuals in each age cohort in the two simulations; in other words, each additional individual in a cohort represents an additional life year lived for that cohort. For this measure, age cohorts are smaller, and the total population is also smaller, for all years of the *without-CAAA* simulation compared to the *with-CAAA* simulation. The gain from CAAA implementation is therefore positive. Interestingly, individuals less than 30 years of age also experience gains from implementing the CAAA, even though the air pollutant effect is assumed not to apply to those under 30 years of age. In this simulation, more adults of child-bearing age exist in the cleaner, *with-CAAA* scenario, because of the effects of air pollutant mortality risk, meaning more children are born to those cohorts. This effect is quite small early on in the simulation period, but grows rapidly over the course of the simulation, until in 2045 more than 1,500 infants that are born in the *with-CAAA* scenario are not born in the *without-CAAA* scenario, because the prospective parents have succumbed prematurely to the effects of air pollution. Over the course of the full simulation, through 2050, implementation of the CAAA accounts for an estimated 120 million additional life years lived in the US population.[135]

Exhibit 7-4 provides estimates of the increase in period life expectancy from the model. Period life expectancy is constructed using age-specific mortality rates for a single year, with no allowance for projected changes in mortality – it is sometimes summarized as the life-expectancy at a certain age as if the individual were to experience the mortality risk of other cohorts alive at that time. In fact all individuals instead will experience a future, unknown risk of mortality that unfolds through their lifetime, but period life expectancy is the methodology that is used to calculate the life expectancy statistics that are generally reported by the CDC, so we report it here.[136] Effects on life expectancy are immediately experienced across all cohorts, and grow rapidly to a gain in the *with-CAAA* scenario of approximately 0.7-0.9 years per individual for all cohorts up to about age 60. Interestingly, while it is typically stated that older cohorts are the main recipients of the benefits of cleaner air, the life expectancy gains among older cohorts are actually

[135] This estimate represents the cumulative life years across the entire study period (i.e., a sum of all of the additional life years accrued in each individual year between 1990 and 2050. Therefore, this estimate does not match the results presented in Exhibit 7-3, which only presents annual life year results in 5-year increments.

[136] The model also calculates cohort conditional life expectancy. Cohort life expectancy is constructed using age-specific mortality rates that reflect projected changes in mortality in future years. In our case, differences in cohort conditional life expectancy reflect our projection of changes in air pollutant-induced mortality risk. The cohort conditional life expectancy tables show an almost immediate gain in life expectancy among younger cohorts because of the anticipated much cleaner air through their lifetime, but those results are of course dependent on our projection of future air quality.

EXHIBIT 7-2. CHANGE IN NUMBER OF DEATHS BY AGE COHORT MOVING FROM *WITH-CAAA* TO *WITHOUT-CAAA* SCENARIO

AGE COHORT	1990	1995	2000	2005	2010	2015	2020	2025	2030	2035	2040	2045
0 to 4	0	0.088	0.62	1.3	1.3	1.5	1.8	2.1	2.2	2.3	2.3	2.3
5 to 9	0	0	0	0.04	0.10	0.12	0.13	0.15	0.18	0.19	0.19	0.20
10 to 14	0	0	0	0	0.037	0.11	0.13	0.14	0.16	0.19	0.21	0.22
15 to 19	0	0	0	0	0.0081	0.13	0.38	0.48	0.54	0.63	0.75	0.84
20 to 24	0	0	0	0	0	0.014	0.18	0.47	0.57	0.64	0.75	0.89
25 to 29	0	0	0	0	0	0	0.013	0.18	0.48	0.58	0.66	0.77
30 to 34	0	(490)	(810)	(1,100)	(1,400)	(1,700)	(2,000)	(1,900)	(1,800)	(1,800)	(1,800)	(1,800)
35 to 39	0	(650)	(1,300)	(1,600)	(1,900)	(2,200)	(2,500)	(2,600)	(2,400)	(2,200)	(2,200)	(2,300)
40 to 44	0	(780)	(1,900)	(2,400)	(2,600)	(2,800)	(3,000)	(3,200)	(3,300)	(3,100)	(2,800)	(2,800)
45 to 49	0	(910)	(2,500)	(3,400)	(4,100)	(4,200)	(4,300)	(4,400)	(4,500)	(4,500)	(4,200)	(3,800)
50 to 54	0	(1,100)	(3,100)	(4,700)	(6,100)	(6,800)	(6,700)	(6,500)	(6,300)	(6,500)	(6,400)	(6,000)
55 to 59	0	(1,300)	(3,700)	(6,200)	(8,200)	(10,000)	(11,000)	(10,000)	(9,400)	(9,100)	(9,400)	(9,200)
60 to 64	0	(1,900)	(4,500)	(7,300)	(11,000)	(13,000)	(16,000)	(16,000)	(14,000)	(13,000)	(13,000)	(13,000)
65 to 69	0	(2,800)	(6,000)	(8,500)	(12,000)	(17,000)	(20,000)	(23,000)	(22,000)	(20,000)	(18,000)	(18,000)
70 to 74	0	(3,700)	(8,200)	(10,000)	(12,000)	(16,000)	(22,000)	(25,000)	(27,000)	(26,000)	(23,000)	(22,000)
75 to 79	0	(4,100)	(10,000)	(12,000)	(13,000)	(15,000)	(19,000)	(24,000)	(26,000)	(28,000)	(27,000)	(25,000)
80 to 84	0	(4,200)	(9,700)	(12,000)	(12,000)	(13,000)	(14,000)	(16,000)	(19,000)	(20,000)	(22,000)	(23,000)
85 to 89	0	(3,300)	(7,200)	(6,800)	(6,900)	(6,200)	(5,600)	(4,500)	(4,000)	(4,500)	(5,000)	(6,400)
90 to 94	0	(1,800)	(2,700)	(820)	1,100	3,400	5,300	7,500	9,700	13,000	16,000	18,000
95 to 99	0	(480)	160	1,800	4,700	8,000	12,000	15,000	17,000	20,000	25,000	33,000
100+	0	(76)	300	1,100	2,800	5,400	8,800	13,000	18,000	21,000	25,000	31,000
Total Change in Deaths:	0	(28,000)	(61,000)	(74,000)	(83,000)	(92,000)	(100,000)	(100,000)	(95,000)	(86,000)	(70,000)	(51,000)

Note: Results in the table are rounded to two significant figures.

EXHIBIT 7-3. ESTIMATED LIFE YEARS GAINED AS A RESULT OF CAAA IMPLEMENTATION

AGE COHORT	1990	1995	2000	2005	2010	2015	2020	2025	2030	2035	2040	2045
0 to 4	0	17	240	670	850	1,000	1,300	1,600	1,900	2,100	2,300	2,600
5 to 9	0	0	17	240	670	850	1,000	1,300	1,600	1,900	2,100	2,300
10 to 14	0	0	0	17	230	670	850	1,000	1,300	1,600	1,900	2,100
15 to 19	0	0	0	0	17	230	670	850	1,000	1,300	1,600	1,900
20 to 24	0	0	0	0	0	17	230	660	840	1,000	1,300	1,600
25 to 29	0	0	0	0	0	0	17	230	660	840	1,000	1,300
30 to 34	0	460	1,200	2,000	2,400	3,100	3,600	3,800	3,700	4,100	4,400	4,500
35 to 39	0	890	4,100	6,900	9,100	11,000	13,000	15,000	15,000	13,000	14,000	14,000
40 to 44	0	1,100	6,000	13,000	17,000	20,000	23,000	27,000	29,000	28,000	26,000	26,000
45 to 49	0	1,200	7,600	19,000	28,000	32,000	37,000	41,000	46,000	47,000	45,000	41,000
50 to 54	0	1,400	9,500	25,000	41,000	54,000	58,000	62,000	66,000	72,000	73,000	69,000
55 to 59	0	1,800	11,000	31,000	55,000	79,000	96,000	98,000	100,000	100,000	110,000	110,000
60 to 64	0	2,600	14,000	37,000	71,000	110,000	140,000	160,000	160,000	150,000	150,000	160,000
65 to 69	0	3,900	20,000	44,000	82,000	140,000	190,000	240,000	250,000	240,000	230,000	230,000
70 to 74	0	5,300	28,000	58,000	94,000	150,000	230,000	300,000	360,000	370,000	340,000	330,000
75 to 79	0	6,100	36,000	79,000	120,000	160,000	240,000	350,000	430,000	490,000	500,000	460,000
80 to 84	0	6,600	39,000	94,000	140,000	180,000	240,000	330,000	460,000	550,000	620,000	630,000
85 to 89	0	5,900	36,000	87,000	150,000	200,000	230,000	290,000	390,000	530,000	620,000	700,000
90 to 94	0	3,900	24,000	62,000	110,000	160,000	200,000	240,000	290,000	380,000	510,000	600,000
95 to 99	0	1,600	10,000	27,000	53,000	85,000	120,000	160,000	180,000	220,000	290,000	390,000
100+	0	490	2,800	7,600	18,000	35,000	60,000	93,000	130,000	160,000	200,000	270,000
Total Life Years Gained	0	43,000	250,000	590,000	980,000	1,400,000	1,900,000	2,400,000	2,900,000	3,400,000	3,800,000	4,100,000

Note: Results in the table are rounded to two significant figures.

EXHIBIT 7-4. INCREASE IN PERIOD CONDITIONAL LIFE EXPECTANCY ATTRIBUTABLE TO THE CLEAN AIR ACT

AGE COHORT	1990	1995	2000	2005	2010	2015	2020	2025	2030	2035	2040	2045
0	0	0.15	0.36	0.52	0.64	0.76	0.86	0.90	0.90	0.91	0.90	0.89
10	0	0.15	0.36	0.52	0.65	0.76	0.86	0.90	0.91	0.91	0.91	0.90
20	0	0.15	0.36	0.52	0.65	0.76	0.87	0.90	0.91	0.91	0.91	0.90
30	0	0.15	0.36	0.53	0.65	0.77	0.87	0.91	0.92	0.92	0.91	0.90
40	0	0.14	0.35	0.51	0.63	0.74	0.84	0.88	0.89	0.89	0.88	0.87
50	0	0.13	0.32	0.47	0.59	0.70	0.79	0.83	0.84	0.84	0.84	0.83
60	0	0.12	0.29	0.42	0.53	0.63	0.71	0.75	0.76	0.77	0.76	0.76
70	0	0.094	0.23	0.35	0.44	0.52	0.59	0.62	0.64	0.64	0.64	0.64
80	0	0.067	0.17	0.25	0.32	0.38	0.43	0.46	0.47	0.48	0.48	0.48
90	0	0.040	0.10	0.15	0.19	0.22	0.25	0.26	0.27	0.27	0.27	0.26
100+	0	0	0	0	0	0	0	0	0	0	0	0

Note: Results in the table are rounded to two significant figures.

truncated because older cohorts may die of something else before experiencing the full benefit from air pollution reduction. Instead, in life expectancy terms, younger cohorts experience the greatest gains.

7.5 DISCUSSION

The Project Team's application of the population simulation model illustrates additional, supplementary characterizations of the benefits of the CAAA, as well as new insights not available from a static approach. They demonstrate the substantial effect of the CAAA on population unfolding through time, and add insights into the life expectancy gains attributed to cleaner air.

Our results for the CAAA simulation are not directly comparable to those from BenMAP – our results reflect a long-term trajectory of improved air quality; and because the effects of changes in exposure are lagged over time as the risk is reduced, our results for any given year represent the cumulative effect of overlapping lagged mortality risk changes from multiple years. It is nonetheless possible to design experiments with the population simulation model that approximate a BenMAP result, in particular for the life-years lost/gained metric. To compare the BenMAP and population simulation approaches and estimate the impact of using a dynamic versus static population approach, we estimated the long-term effect of a one year change in exposure in 2010 and 2020 comparable to the one-year national population-weighted change that is developed in the BenMAP runs for those two target years.

The results of our comparison suggest that the effect of using a dynamic model is substantial, as illustrated in Exhibit 7-5 below. The total effect of using a dynamic approach is roughly a factor of three – in 2020, for example, the dynamic approach estimates almost 9 million life years saved through 2050, while the BenMAP approach estimates just more than 3 million life years saved for a single year's exposure improvement. The results by cohort could be somewhat misleading, as they reflect different approaches to allocating life year gains among cohorts. BenMAP attributes life year gains to the cohort that is of a certain age in the year in which exposure changes (in this case, either 2010 or 2020), regardless of when those life-year gains accrue, while the population simulation model attributes gains to the cohort in the year they are experienced. This difference in approach means that BenMAP attributes more of the life-year gains to younger cohorts, but both approaches are simulating the same effect. The main difference is that the population simulation approach incorporates the effects of a dynamically growing population as a result of the gain in air pollution – the end result is that the life-years-gained measure of the mortality benefit of clean air is likely underestimated by the static approach, and perhaps by a substantial margin.

EXHIBIT 7-5. COMPARISON OF LIFE YEARS GAINED FROM A ONE-YEAR EXPOSURE CHANGE FOR BENMAP AND POPULATION SIMULATION MODEL

AGE COHORT		BENMAP RESULTS		POPULATION SIMULATION MODEL	
START AGE	END AGE	2010	2020	2010	2020
30	34	70,000	94,000	11,000	12,000
35	44	220,000	260,000	110,000	130,000
45	54	390,000	420,000	300,000	320,000
55	64	560,000	770,000	700,000	720,000
65	74	530,000	890,000	1,400,000	1,600,000
75	84	480,000	610,000	2,300,000	2,600,000
85	99	220,000	300,000	2,900,000	3,500,000
	Total	2,500,000	3,300,000	7,700,000	8,900,000

CHAPTER 8 | VALUATION UNCERTAINTY

Another key factor contributing to uncertainty in the monetized benefit estimates associated with the Clean Air Act Amendments of 1990 (CAAA) is uncertainty in the "value of statistical life" (VSL) estimates that we apply to reductions in premature mortality. The VSL is a summary measure of willingness-to-pay (WTP) values for small reductions in mortality risk experienced by a large number of people. The VSL approach applies information from several published value-of-life studies to determine a reasonable monetary value of preventing premature mortality. EPA's primary benefits estimate is calculated using a distribution of VSLs based on 26 studies that assumes a Weibull distribution with a mean of $4.8 million in 1990$ ($7.4 million in 2006$).

However, the literature on VSL is extensive, and studies have measured VSL using different methodological approaches (e.g., revealed versus stated preference) on a variety of study populations (e.g., workers versus a general population sample) in a variety of different risk contexts (e.g., fatal workplace accidents versus mortality risk from disease). In addition, several meta-analyses of the literature have been conducted in an attempt to synthesize the literature, including those by Viscusi and Aldy (2003), Mrozek and Taylor (2002) and Kochi et al. (2006).[137] In this chapter, we explore the implications of assuming alternative distributions for VSL on the net present value (NPV) monetized estimates of CAAA-related reductions in premature mortality.

8.1 UNCERTAINTY IN ECONOMIC VALUATION

The Project Team explored the uncertainty in the estimated economic value of avoided deaths due to $PM_{2.5}$ by applying several different estimates of VSL to the mortality incidence results from the core scenarios for each of the three target years. We compare all estimates against the primary estimate, which is based on a Weibull distribution of VSL values derived from 26 studies. We generated alternative NPV mortality benefits estimates using the following alternative VSL distributions:[138]

---

[137] Viscusi, W. K. and J. E. Aldy. 2003. The Value of a Statistical Life: A Critical Review of Market Estimates throughout the World. AEI-Brookings Joint Center for Regulatory Studies. Washington, DC. January.; Mrozek, J.R., Taylor, L.O. 2002. What Determines the Value of Life? A Meta-Analysis. *Journal of Policy Analysis and Management* 21(2): 253-270.; and Kochi, I., Hubbell, B., Kramer, R. 2006. An Empirical Bayes Approach to Combining and Comparing Estimates of the Value of a Statistical Life for Environmental Policy Analysis. *Environment and Resource Economics* 34: 385-406.

[138] Note that the VSL estimates are presented as they were originally published. All of our results are presented in 2006$. After applying the VSLs to the mortality incidence estimates, we converted the benefits estimates from their original currency year to 2006$ using inflation adjustment factors from BenMAP (Abt Associates, Inc. (2008). BenMAP User's Manual. Prepared for the U.S. EPA's Office of Air Quality Planning and Standards, Research Triangle Park, NC. September.)

- A VSL distribution derived from estimates reported in a 2003 meta-analysis by Viscusi and Aldy (specifically, the mean predicted VSL and confidence interval for the U.S. sample, derived using Model 5 as reported in Table 8). This specific estimate was selected because it provided the best model fit to the data, had relatively tight confidence bounds, and reduced non-normality in the error term by using Huber weighting. The Project Team applied this estimate by assuming a lognormal distribution with a geometric mean of $6.3 million (in 2000$).[139]
- An estimate from Viscusi and Aldy (2003) Model 2 from Table 8, assuming a log-normal distribution with a geometric mean of $5.8 million (in 2000$)[140];
- The estimate used in the recent PM National Ambient Air Quality Standards (NAAQS) Regulatory Impact Analysis (RIA) assuming a normal distribution with a mean of $5.5 million (in 2000$);[141] and
- An estimate from a wage-risk study by Viscusi (2004) assuming a truncated normal distribution with a mean of $4.8 million, a minimum of $2.3 million, and a maximum of $7.1 million (in 1997$ and at 1997 income levels).[142,143]

We generated NPV estimates of monetized reductions in premature mortality discounted to each target year using the same simulation sampling approach applied in the primary analysis, and assumed that avoided mortality benefits are accrued over time in the pattern described in the 20-year cessation lag model advocated by the Advisory Council for Clean Air Compliance Analysis (Council).[144] EPA's Benefits Analysis and Mapping Program (BenMAP) uses statistical sampling methods to generate a mortality valuation distribution that integrates uncertainty in total avoided mortality with VSL uncertainty described by a user-specified VSL distribution. We then scale this distribution using a

---

[139] The chosen model is semi-log in form and reports a 95 percent confidence interval that is consistent with a log-normally distributed VSL, although the paper itself does not report a specific VSL distribution.

[140] As is the case with the VSL estimate from Model 5, the chosen model is semi-log in form and reports a 95 percent confidence interval that is consistent with a log-normally distributed VSL, although the paper itself does not report a specific VSL distribution.

[141] http://www.epa.gov/ttn/ecas/ria.html (see Chapter 5).

[142] This estimate was derived by Dr. Joseph Aldy of Resources for the Future by taking 100,000 random draws of two normal distributions: 1) a distribution of coefficient estimate of on-the-job mortality risk variables from Viscusi (2004); and 2) a distribution of workers' hourly wages. He then took the product of each pair of draws. According to Aldy, the 95 percent confidence bounds of the resulting distribution were "virtually identical" to the result assuming the product is normally distributed. Therefore, we assumed that the distribution was normally distributed with a mean of $4.8 million, as reported by Aldy, truncated at the minimum and maximum values also reported by Aldy. See Appendix A from the report, *Valuing Mortality Risk Reductions inHomeland Security Regulatory Analyses,* Final Report, June 2008, Prepared by Lisa A. Robinson, Independent Consultant for Elena Ryan, U.S. Customs and Border Protection, Department of Homeland Security, under subcontract to Jennifer Baxter and Henry Roman, Industrial Economics Incorporated.

[143] Viscusi, W.K. (2004). The value of life: Estimates with risks by occupation and industry. Economic Inquiry 42(1): 29-48.

[144] Science Advisory Board (2004). Advisory on Plans for Health Effects Analysis in the Analytical Plan for EPA's Second Prospective Analysis—Benefits and Costs of the Clean Air Act, 1990-2020: Advisory by the Health Effects Subcommittee of the Advisory Council on Clean Air Compliance Analysis. EPA-SAB-COUNCIL-ADV-04-002.

target-year specific adjustment factor that accounts for income growth over time,[145] the effect of cessation lag on accrual of the mortality benefits from air pollution changes in the target year, and the effect of discounting VSL values for mortality benefits expected to occur after the target year. The result of this scaling calculation is a distribution of NPVs for avoided mortality benefits, based on an assumed 20-year distributed cessation lag for PM mortality effects and application of a 5 percent discount rate.

We also generated alternative results substituting discount rates of 3 and 7 percent, in addition to the default discount rate of 5 percent.[146]

8.2 RESULTS

8.2.1 ALTERNATIVE VSLs

Exhibit 8-1 provides a table of valuation results for the three target years using alternative VSL distributions. Exhibit 8-2 presents these same results using box plots that illustrate alternative results distributions.

- Overall, the mean valuation estimates from BenMAP for premature mortality due to CAAA-related changes in $PM_{2.5}$ using the alternative estimates of VSL range from 20 percent lower to equivalent to our primary estimate when applying the Viscusi et al., 2004 and Viscusi and Aldy (2003) Model 5 distributions, respectively.
- The spread of the confidence bounds of the VSL estimates vary, with the distribution of the primary estimate (Weibull) having the largest spread and the Viscusi (2004) results having the smallest spread.

8.2.2 ALTERNATIVE DISCOUNT RATES

Exhibit 8-3 provides the economic valuation results for each target year, applying alternative discount rates to calculate the NPV. Exhibit 8-4 provides a graphical representation of the 90 percent confidence bounds around each of the benefits estimates. Applying alternative discount rates has little effect on the benefits estimates; applying a discount rate of 7 percent results in benefits that are four percent lower than the default and applying a 3 percent discount rate results in a benefits estimate four percent higher than the default.

[145] Income adjustment factors reflecting future income growth projections and the income elasticity of VSL were obtained from BenMAP (Abt Associates, Inc. (2008). BenMAP User's Manual. Prepared for the U.S. EPA's Office of Air Quality Planning and Standards, Research Triangle Park, NC. September.)

[146] Alternative discount rates of three and seven percent are recommended in U.S. EPA (2000). *Guidelines for Preparing Economic Analyses*, EPA 240-R-00-003, September.

EXHIBIT 8-1. RELATIVE PM/MORTALITY VALUATION RESULTS USING ALTERNATIVE ESTIMATES OF VSL (MILLIONS OF 2006$)

VSL ESTIMATE	PERCENTILE 5	MEAN	PERCENTILE 95
Weibull Distribution (Primary) - 2000	**$66,000**	**$710,000**	**$2,200,000**
Weibull Distribution (Primary) - 2010	**$110,000**	**$1,200,000**	**$3,600,000**
Weibull Distribution (Primary) - 2020	**$170,000**	**$1,700,000**	**$5,300,000**
	Percent Change from Mean Primary Estimate*		
Viscusi and Aldy (2003) - Model 5	-80%	0%	122%
Viscusi and Aldy (2003) - Model 2	-82%	-7%	108%
Normal Distribution	-87%	-14%	122%
Viscusi et al. (2004)	-85%	-20%	71%

* All values in the table represent the percent change from the mean primary estimate. Percent change estimates do not vary by target year.

EXHIBIT 8-2. BOX-PLOT OF 90 PERCENT CONFIDENCE BOUNDS FOR ALTERNATIVE VSL RESULTS

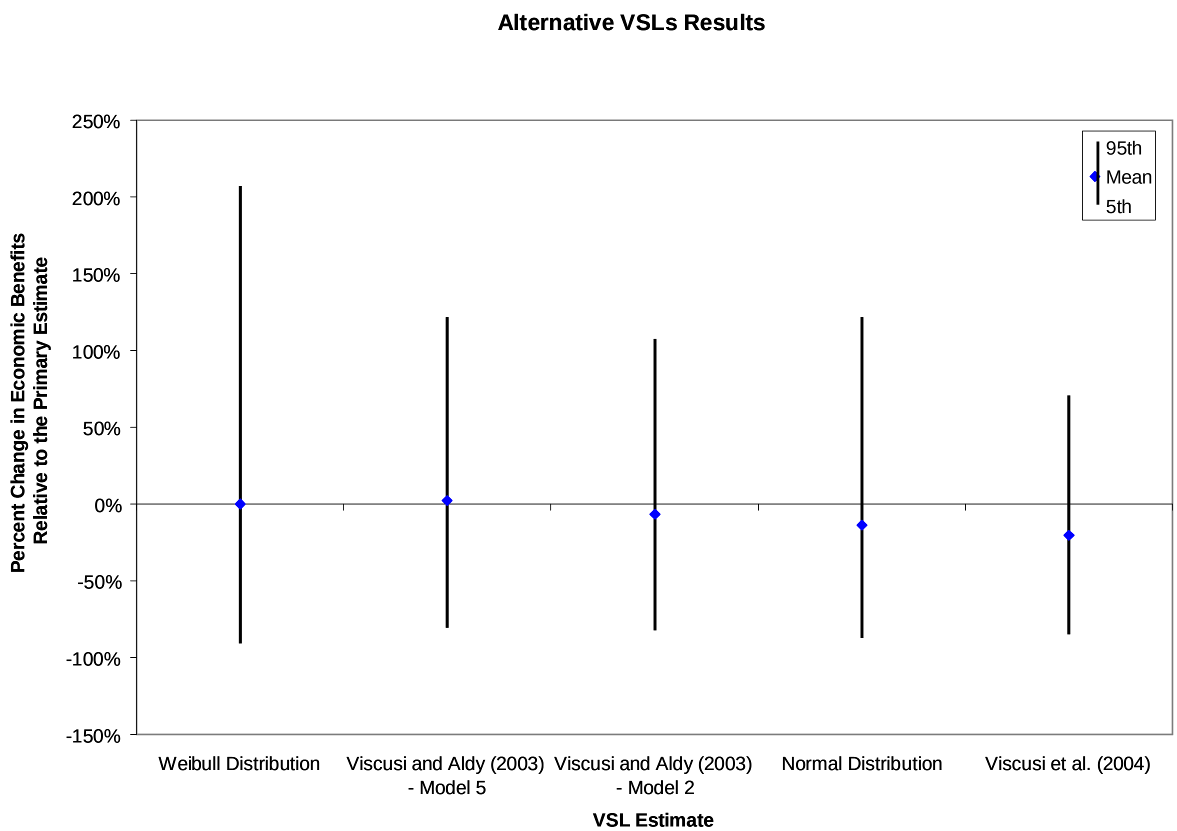
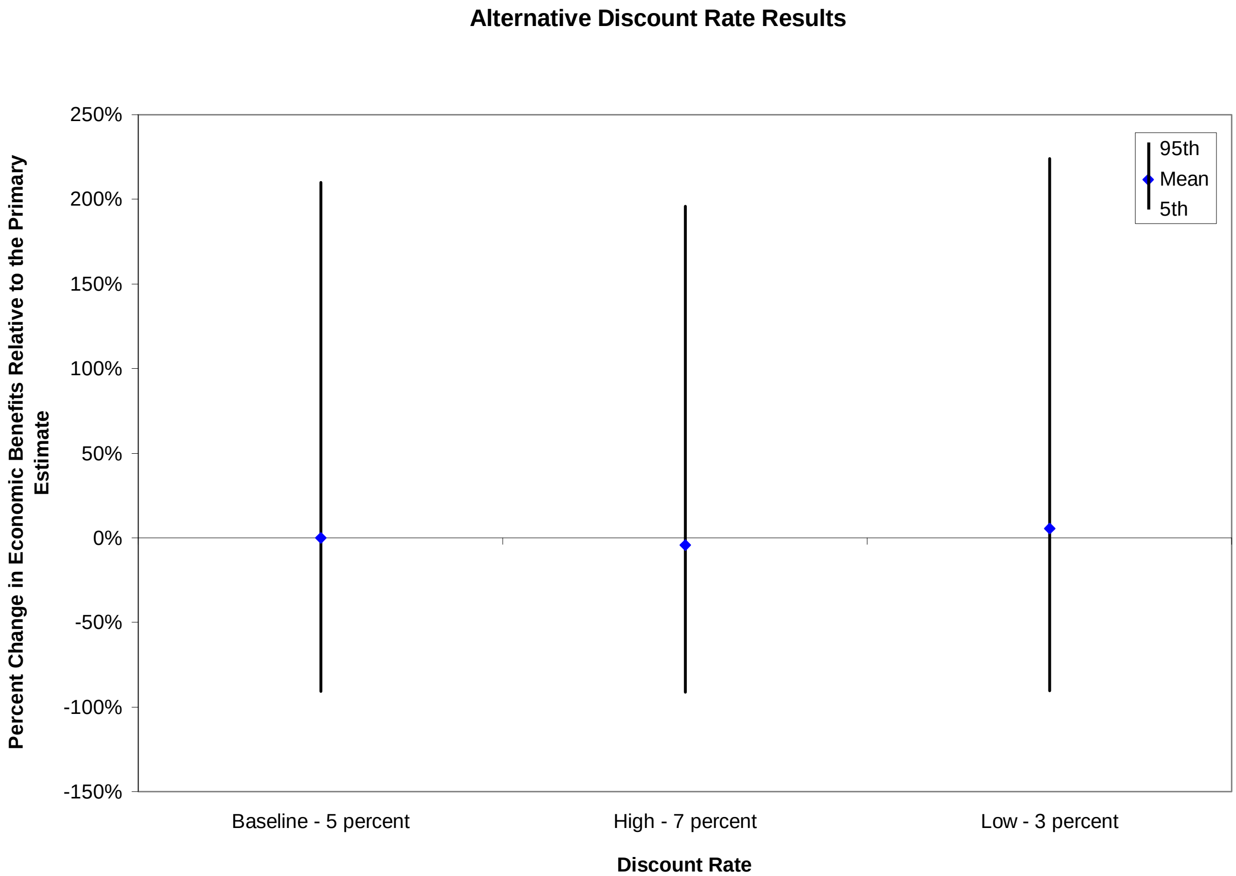


EXHIBIT 8-3. RELATIVE PM/MORTALITY VALUATION RESULTS USING ALTERNATIVE DISCOUNT RATES (MILLIONS OF 2006$)

VSL ESTIMATE	PERCENTILE 5	MEAN	PERCENTILE 95
Baseline (5 percent) - 2000	**$66,000**	**$710,000**	**$2,200,000**
Baseline (5 percent) - 2010	**$110,000**	**$1,200,000**	**$3,600,000**
Baseline (5 percent) - 2020	**$170,000**	**$1,700,000**	**$5,300,000**
	Percent Change from Mean Primary Estimate*		
High (7 percent)	-91%	-4%	191%
Low (3 percent)	-90%	4%	223%

***** All values in the table represent the percent change from the mean primary estimate. Percent change estimates do not vary by target year.

EXHIBIT 8-4. BOX-PLOT OF 90 PERCENT CONFIDENCE BOUNDS FOR ALTERNATIVE DICSOUNT RATE RESULTS



CHAPTER 9 | CONCLUSIONS

This chapter summarizes the advances in the quantitative treatment of uncertainty in the Second Prospective Section 812 Study of the Clean Air Act Amendments (CAAA) and their implications for interpreting the benefit and cost results.

9.1 ADVANCES IN QUANTITATIVE ANALYSES

This uncertainty analysis has made significant incremental advances in the quantitative treatment of uncertainty in several elements of the analytical chain of the second prospective analysis of the benefits and costs of the Clean Air Act. Areas of advancement include:

- **Emissions.** Using EPA's cutting-edge meta-model, the Response Surface Model (RSM), as a cost-effective, reduced-form substitute for Community Multiscale Air Quality Model (CMAQ), we were able to evaluate the impact of marginal changes in emissions in each of the five major particulate matter (PM) source categories on PM levels nationwide and on estimates of avoided mortality due to the CAA. These offline analyses allow us to compare the marginal benefits of additional reductions in each sector, and give us some sense of the potential sensitivity of results to changes in emissions. In addition, we conducted an analysis of the impacts of scenario uncertainty in both the *with*- and *without-CAAA* cases on emissions from the Electric Generating Unit (EGU) sector in 2000.

- **Concentration-Response.** We evaluated both parameter and model uncertainty in concentration-response (C-R) function estimates for PM-related mortality, replacing the primary C-R function with functions with alternative C-R coefficient distributions from individual studies from the literature and with the 12 EPA expert elicitation (EE)-based functions that present alternative coefficient distributions and, in some cases, alternative shapes of the PM-mortality C-R function. In addition, we evaluated parameter uncertainty in the C-R function for ozone mortality.

- **Cessation Lag.** We completed an evaluation of the effects on monetized benefits of model uncertainty in the temporal realization of avoided mortality benefits following reductions in PM exposure (i.e., cessation lag). This included assessment of the impacts of assuming alternative forms for the cessation lag structure instead of the primary 20-year step function, including a more rapid 5-year step function and a variety of smooth functions that incorporate information from both PM intervention studies and long- term cohort studies of PM mortality.

- **Dynamic Population Modeling.** We also assessed the implications of an alternative damage function approach that incorporates dynamic changes in population over time using a life-table approach to benefit assessment. Though the model employed a simplified treatment of exposure changes due to the CAAA, it nonetheless provided useful insights into the potential magnitude of the CAAA's effect on population size, life-years gained, and life expectancy.
- **Valuation.** We assessed the sensitivity of monetized results to an array of alternative distributions from the published literature for value of statistical life (VSL) and alternative assumptions about the discount rate applied to VSL for avoided mortality benefits expected to accrue in future years.
- **Direct Costs.** We assessed several sources of uncertainty in direct cost estimates, including scenario uncertainty in predictions of the future composition and fuel economy of the U.S. vehicle fleet and parameter uncertainty in three factors: (1) the assumed rate at which experience applying control technologies reduces control costs; (2) vehicle failure rates associated with inspection and maintenance (I&M) programs; and (3) the cost per ton of unidentified local pollution controls.

For additional uncertainties, we developed revised qualitative uncertainty tables that update the tables presented in the First Prospective 812 Study. These tables describe the uncertainty; present our assessment, where possible, of the likely direction of bias in net benefits associated with that uncertainty; and give our characterization of the potential significance of the uncertainty ("potentially major" if the effect could exceed five percent of current net benefits, "probably minor" if less than five percent, or "unknown"). In addition, this report included a detailed and extensive evaluation of the potential for notional sensitivity analyses of the impacts of uncertainty about the relative toxicity of the various components that comprise $PM_{2.5}$ and concluded that significant data gaps in both toxicology and epidemiology preclude the development of useful, policy-relevant analysis at this time.

9.2 SUMMARY OF KEY UNCERTAINTIES

Exhibit 9-1 presents a tabular summary of the results of the analyses presented in this report for both costs and benefits. Exhibit 9-2 presents a graphical illustration of the impacts of effect of alternative assumptions and models on the central estimate and distribution of monetized avoided mortality benefits, the primary contributor to monetized benefits.

EXHIBIT 9-1. QUANTITATIVE ANALYSES OF UNCERTAINTY IN THE 812 SECOND PROSPECTIVE ANALYSIS

FACTOR	TYPE OF UNCERTAINTY EVALUATED	ALTERNATIVE ASSUMPTIONS	IMPACT OF ALTERNATIVE ASSUMPTIONS ON 2020 PRIMARY ESTIMATE
UNCERTAINTIES RELATED TO COST ESTIMATES			
Unidentified controls (Ch 2)	Parameter	Alternate assumption about the threshold for, and cost of, applying unidentified local controls to achieve NAAQS compliance ($10,000/ton).	-18% of local control costs; -2.1% of total costs
I&M program vehicle failure rates(Ch 2)	Parameter	Alternative assumption about failure rates for I&M program testing based on NRC (2001).	-12% for mobile source costs; -6.5% of total costs
Learning curve assumptions (Ch 2)	Parameter	Alternate assumptions about the learning rate (5 and 20%)	-6.0% to 3.2% of total costs
Fleet composition and fuel efficiency (Ch 2)	Scenario	Alternate assumption about future fleet composition and fuel efficiency using AEO 2008.	-3.6% for mobile source costs; -2.0% of total costs
UNCERTAINTIES RELATED TO BENEFITS ESTIMATES			
Alternate C-R function for PM (Ch 4)[a]	Parameter	Alternative C-R functions – two from empirical literature (Pope et al., 2002 and Laden et al., 2006) and 12 subjective estimates from the expert elicitation study	-83% to 76%, Based on most extreme estimates from PM EE study. Rest of alternatives range from -44% to 40%
Emissions from EGU sources (Ch 3)	Scenario	Use continuous emissions monitoring (CEM) data in place of Integrated Planning Model (IPM) results, coupled with alternative counterfactual consistent with CEM approach.	+50% in 2000 Due almost entirely to the impact of the alternative *without-CAAA* scenario.
PM/Mortality Cessation lag (Ch 6) [a]	Model and parameter	Alternative lag structures – one step function and a series of smooth functions (based on an exponential decay). Smooth functions in some cases also require change in C-R coefficient.	-23% to 16% when using primary C-R function. -52 to 50% when also changing C-R function.
VSL (Ch 8) [a]	Parameter	Alternative VSL estimates	-20% to 0%
Discount rates (Ch 8) [a]	Parameter	Alternate discount rates (5% and 7%)	-4% to 4%
Alternate C-R function for ozone (Ch 4)	Parameter	Alternative C-R functions – three from multi-city studies and three meta-analyses	0% for total mortality benefits. -63% to 66% For ozone-related mortality.

FACTOR	TYPE OF UNCERTAINTY EVALUATED	ALTERNATIVE ASSUMPTIONS	IMPACT OF ALTERNATIVE ASSUMPTIONS ON 2020 PRIMARY ESTIMATE
Emissions changes by emitting sector (Ch 3)	Scenario	Altering each sector-specific emissions by 10 percent	$/ton marginal benefit for proportional EGU sector reductions is about 3 times that for nonroad and on-road sectors, and 50% higher than that for area and non-EGU point source sectors.
Differential toxicity of PM components (Ch 5)	Parameter	Potential alternative estimates of toxicity for specific PM components	N/A. No quantitative sensitivity analysis performed due to significant data gaps.
Dynamic population modeling (Ch 7)	Model	Incorporation of dynamic population estimates to calculate life years gained and changes in life expectancy	N/A. Life years gained and changes in life expectancy are supplemental estimates of PM/mortality effects and cannot be directly compared to the primary estimate.

9.2.1 COST UNCERTAINTIES

Exhibit 9-1 shows that the impact of our alternative assumptions about mobile source cost parameters, learning curves, and unidentified local control costs each have relatively modest impacts on total costs, with the I&M failure rate and learning curve assumptions have slightly more of an impact on total costs.[147] In addition, the assumptions underlying our primary cost estimates tend to be conservative; most of the alternatives decrease total compliance costs and none increase costs more than about three percent.

9.2.2 BENEFIT UNCERTAINTIES

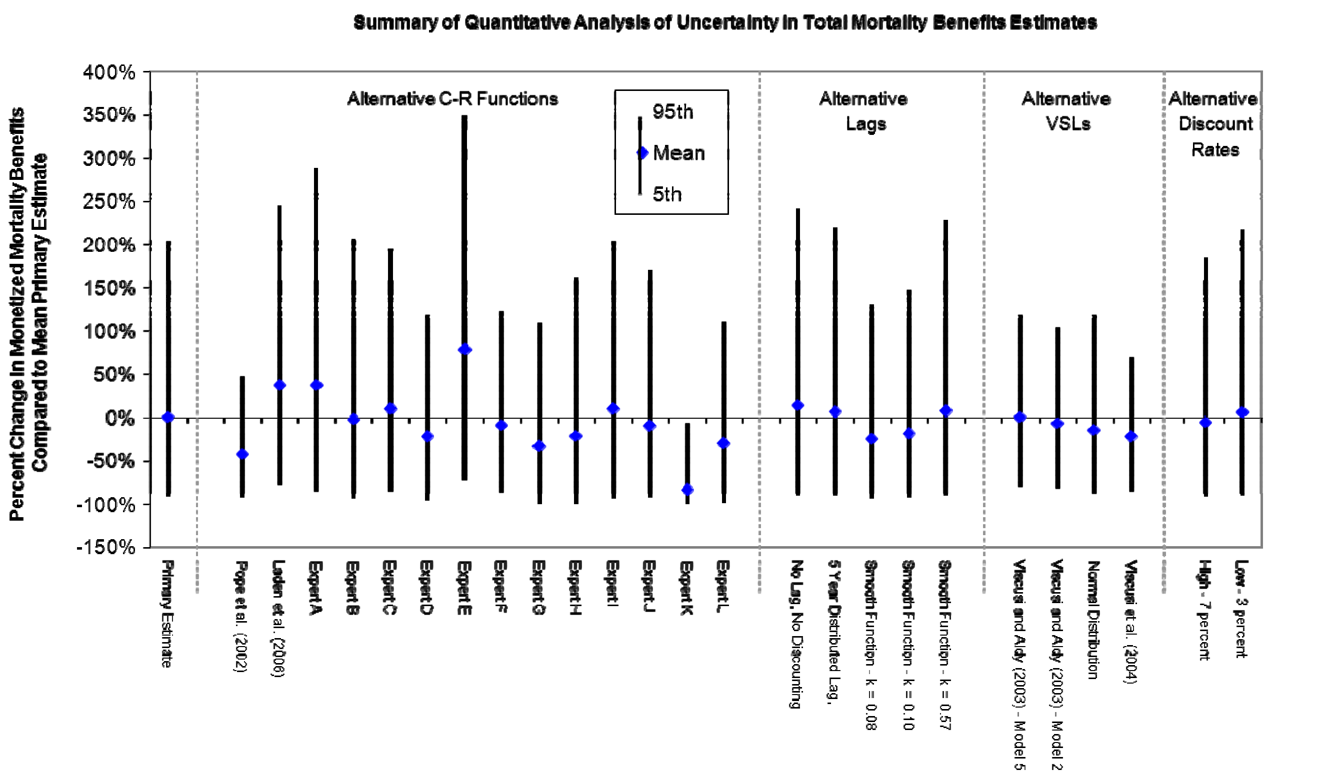
On the benefits side, Exhibits 9-1 and 9-2 show that the most influential assumptions affecting benefits are the choice of the C-R function, the cessation lag model for the accrual of benefits, and the VSL distribution. While the two most extreme results from EPA's EE study imply substantial effects of C-R choice (about 80 percent in either direction) most of the alternatives from the EE study and the published epidemiological studies suggest effects on benefits of about 40 percent or less in either direction. By themselves, longer cessation lag alternatives can reduce monetized benefits by as much as a 23 percent and if coupled with a change in the C-R function, by close to half; however, the Council suggested much of the risk reduction benefits from $PM_{2.5}$ controls are more

[147] The estimate of the impact on total costs is derived from the relative contribution of the affected cost sector to the overall costs of compliance, assuming all other sectors are unaffected.

likely to accrue sooner rather than later. Accelerating benefits increases benefits by about 16 percent when maintaining the same C-R function, but could increase them by as much as half when using a smooth function based on the Laden Six Cities follow-up effect estimate. VSL distribution choices in one case produce the same central estimate; in others reduce VSL between 7 and 20 percent.

A review of the box plots in Exhibit 9-2 for the factors that have the greatest potential to change the central estimate shows that most of the alternatives do not have a dramatic effect on the spread of uncertainty. Some alternatives suggest the high end of the distribution could be lower, including all of the alternative VSL distributions, which give less weight to higher VSL values than the 26-study Weibull. On the other hand, only a few alternatives (from the EE study) significantly extend the upper end and hardly any extend the lower end, suggesting our primary estimate is unlikely to understate the uncertainty in avoided mortality benefits.

EXHIBIT 9-2. SUMMARY OF QUANTITATIVE ANALYSIS OF UNCERTAINTY IN MONETIZED MORTALITY BENEFITS ESTIMATES



Note: that the Project Team assessed the impact Of alternative ozone C-R functions on the total mortality benefits and found that these did not alter the primary estimate. Therefore, alternative ozone C-R functions are not included in this graph.

9.2.3 ADDITIONAL OBSERVATIONS

Offline modeling of marginal changes in emissions by sector suggests that the EGU sector yields the most benefits at the margin in 2020 (on a dollar per ton basis), followed by area sources, non-EGU point sources, on-road sources, and non-road sources. The benefit per ton ratio in 2020 is about 3:2 for when comparing EGU emissions to area emissions and to non-EGU emissions; the ratio is 3:1 for EGU emissions to both mobile source categories. These results rank the expected sensitivity of benefit results to uncertainties in emissions inventories for these sectors, and could provide perspective on the ordering of priorities for additional reductions in future air regulations.

Scenario uncertainty related to the details of the *without-CAAA* scenario for EGUs, as discussed in Chapter 3, is another potentially significant uncertainty for benefits; use of the Ellerman-based alternative *without-CAAA* scenario in 2000 coupled with the CEM-based *with-CAAA* scenario produces a central estimate of avoided mortality benefits approximately 50 percent greater than the standard scenarios. Given that the differences between the alternative *without-CAAA* scenario RSM runs were often much greater than the differences between the CEM- and IPM-based *with-CAAA* RSM runs, the difference in benefits appears to be due predominantly to the changes in the *without-CAAA* scenario. While we are unable to determine which represents the more accurate counterfactual, the *without-CAAA* scenario we apply for the primary results appears to be the more conservative choice.

The 812 Project Team's use of a damage model with dynamic population simulation yielded striking results that demonstrate the substantial effect of the CAAA on population over time and provide useful insights into gains in life expectancy due to the CAAA. Use of a dynamic model showed an approximate tripling of the expected life years saved due to a single year's exposure improvement, suggesting that the static approach to benefits assessment likely underestimates the mortality benefits of improved air quality, possibly by a substantial margin.

A comparison of the qualitative uncertainty tables from the First and Second Prospective studies indicates that significant advancements over the First Prospective include the use of improved monitoring data for $PM_{2.5}$, an improved understanding and treatment of atmospheric chemistry and the composition of $PM_{2.5}$ emissions, and the use of longer-term simulations with integrated modeling of criteria pollutants using CMAQ rather than a collection of separate air quality models. Other potentially major uncertainties affecting benefits estimates in the Second Prospective not mentioned above include the inclusion in the *with-CAAA* scenario of CAIR and CAMR, both of which are being re-tooled by EPA in the wake of court rulings.

APPENDICES

APPENDIX A | QUALITATIVE UNCERTAINTY ANALYSIS TABLES FROM THE FIRST PROSPECTIVE ANALYSIS

TABLE A-1. KEY UNCERTAINTIES ASSOCIATED WITH COST ESTIMATION

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS	LIKELY SIGNIFICANCE RELATIVE TO KEY UNCERTAINTIES ON NET BENEFITS ESTIMATE[1]
Costs are based on today's technologies. Innovations in future emission control technology and competition among equipment suppliers tend to reduce costs over time.	Underestimate	Probably minor. Available evidence suggests that estimates of pollution control costs based on current engineering can substantially overestimate the ultimate cost incurred, resulting in understanding net benefits.[2]
Uncertainty of final State strategies for meeting Reasonable Further Progress (RFP) requirements.	Underestimate	Probably minor. We apply a conservative estimate for costs of RFP measures. Available evidence for identified RFP measures suggests costs could be as much as 70 percent lower than this value. The bias most likely results in significantly understating net benefits.
Errors in emission projections that form the basis of selecting control strategies and costs in both the IPM and ERCAM models.	Unable to determine based on current information	Probably minor. In many cases, emissions reductions are specified in the regulations, suggesting that errors in the estimation of absolute levels of emissions under Pre- and Post-CAAA scenarios may have only a small impact on cost estimates. The effect on net benefits is unknown.
Exclusion of the impact of economic incentive provisions, including banking, trading, and emissions averaging provisions.	Underestimate	Probably minor. Economic incentive provisions can substantially reduce costs, but the major economic programs for trading of sulfur and nitrogen dioxide emissions are reflected in the analysis.
Incomplete characterization of certain indirect costs, including vehicle owner opportunity costs associated with Inspection and Maintenance Programs and performance degradation issues associated with the incorporation of emission control technology.	Overestimate	Probably minor. Preliminary evidence suggests that the opportunity costs of vehicle owners is most likely small relative to other cost inputs.[3] In addition, it will vary from State to State and is subject to a variety of influencing factors. The potential magnitude of indirect costs associated with performance degradation is more uncertain, because few data currently exist to quantify this effect.

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS	LIKELY SIGNIFICANCE RELATIVE TO KEY UNCERTAINTIES ON NET BENEFITS ESTIMATE[1]
Choice to model direct costs rather than social costs.	Unable to determine based on current information	Probably minor. The relationship of social cost to direct cost estimates is influenced by multiple factors that operate in opposite directions, suggesting the magnitude of the net effect is reduced. Social cost estimates can reflect the net welfare changes across the full range of economic sectors in the U.S., and so may yield higher estimates of costs than a direct cost approach. In addition, social cost estimates can be constructed to reflect the potentially substantial cost magnifying effect of existing tax distortions. Direct cost estimates, however, are likely to overstate costs in the primary market because they do not reflect consumer and producer responses. The extent to which a direct cost estimate will overstate or understate a social cost estimate depends on the magnitude of the "ripple effects" in economic sectors not targeted by a regulation. In addition, assessment of the effect on net benefit estimates must also account for any economy-wide effects of direct benefits (e.g., the broader implications of improving health status, and improving environmental quality).
Use of costs for rules that are currently in draft form (i.e., not yet finalized).	Unable to determine based on current information	Probably minor. Rules that are most important to the overall cost estimate are largely finalized. For example, there is some uncertainty as to how the cap-and-trade program through the SIP process will lower NO_x emissions in an efficient manner. The expected effect on net benefits is minimal.

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS	LIKELY SIGNIFICANCE RELATIVE TO KEY UNCERTAINTIES ON NET BENEFITS ESTIMATE[1]
Exclusion of costs of 7-year and 10-year MACT standards and the residential risk standards for the 2- and 4-year MACT standards.	Unable to determine based on current information	Probably minor. Costs for the 7- and 10-year MACT standards are likely to be less than for the 2- and 4-year standards included in the analysis and the need for, and potential scope and stringency of, future Title III residual risk standards remain highly uncertain. For consistency, benefits of the 7- and 10-year standards and the residual risk standards are also excluded.

1 The classification of each potential source of error reflects the best judgment of the section 812 Project Team. The Project Team assigns a classification of "potentially major" if a plausible alternative assumption or approach could influence the overall monetary benefit estimate by approximately five percent or more; if an alternative assumption or approach is likely to change the total benefit estimate by less than five percent, the Project Team assigns a classification of "probably minor."

2 For more detail, see Harrington et al. (1999).

3 Preliminary evidence based on Arizona's Enhanced I/M program indicates that major components of the programs costs are associated with test and repair costs rather than the costs of waiting and travel for vehicle owners. (Harrington and McConnell, 1999). To date, Enhanced I/M programs have been implemented in only four States.

TABLE A-2. KEY UNCERTAINTIES ASSOCIATED WITH EMISSIONS ESTIMATION

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS ESTIMATE	LIKELY SIGNIFICANCE RELATIVE TO KEY UNCERTAINTIES IN NET BENEFIT ESTIMATE*
$PM_{2.5}$ emissions are largely based on scaling of PM_{10} emissions.	Overall, unable to determine based on current information, but current emission factors are likely to underestimate $PM_{2.5}$ emissions from combustion sources, implying a potential underestimation of benefits.	Potentially major. Source-specific scaling factors reflect the most careful estimation currently possible, using current emissions monitoring data. However, health benefit estimates related to changes in $PM_{2.5}$ constitute a large portion of overall CAAA-related benefits.
Primary $PM_{2.5}$ emissions estimates are based on unit emissions that may not accurately reflect composition and mobility of the particles. For example, the ratio of crustal to primary carbonaceous particulate material likely is high.	Underestimate. The effect of overestimating crustal emissions and underestimating carbonaceous when applied in later stages of the analysis, is to reduce the net impact of the CAAA on primary $PM_{2.5}$ emissions by underestimating $PM_{2.5}$ emissions reductions associated with mobile source tailpipe controls.	Potentially major. Mobile source primary carbonaceous particles are a significant contributor to public exposure to $PM_{2.5}$. Overall, however, compared to secondary $PM_{2.5}$ precursor emissions, changes in primary $PM_{2.5}$ emissions have only a small impact on $PM_{2.5}$ related benefits.
The post-CAAA scenario includes implementation of a region-wide NO_x emissions reduction strategy to control regional transport of ozone that may not reflect the NO_x controls that are actually implemented in a regional ozone transport rule.	Unable to determine based on current information.	Probably minor. Overall, magnitude of estimated emissions reductions is comparable to that in expected future regional transport rule. In some areas of the 37-state region, emissions reductions are expected to be overestimated, but in other areas, NO_x inhibition of ozone leads to underestimates of ozone benefits (e.g., some eastern urban centers).
VOC emissions are dependent on evaporation, and future patterns of temperature are difficult to predict.	Unable to determine based on current information.	Probably minor. We assume future temperature patterns are well characterized by historic patterns, but an acceleration of climate change (warming) could increase emissions.

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS ESTIMATE	LIKELY SIGNIFICANCE RELATIVE TO KEY UNCERTAINTIES IN NET BENEFIT ESTIMATE*
Use of average temperatures (i.e., daily minimum and maximum) in estimating motor-vehicle emissions artificially reduces variability in VOC emissions.	Unable to determine based on current information.	Probably minor. Use of averages will overestimate emissions on some days and underestimate on other days. Effect is mitigated in Post-CAAA scenarios because of more stringent evaporative controls that are in place by 2000 and 2010.
Economic growth factors used to project emissions are an indicator of future economic activity. They reflect uncertainty in economic forecasting as well as uncertainty in the link to emissions.	Unable to determine based on current information.	Probably minor. The same set of growth factors are used to project emissions under both the Pre-CAAA and Post-CAAA scenarios, mitigating to some extent the potential for significant errors in estimating differences in emissions.
Uncertainties in the stringency, scope, timing, and effectiveness of Post-CAAA controls included in projection scenarios.	Unable to determine based on current information.	Probably minor. Future controls could be more or less stringent, wide-reaching (e.g., NO_x reductions in OTAG region - see above), or effective (e.g., uncertainty in realizing all Reasonable Further Progress requirements) than projected. Timing of emissions reductions may also be affected (e.g., sulfur emissions reductions from utility sources have occurred more rapidly than projected for this analysis).
* The classification of each potential source of error reflects the best judgment of the section 812 Project Team. The Project Team assigns a classification of “potentially major” if a plausible alternative assumption or approach could influence the overall monetary benefit estimate by approximately five percent or more; if an alternative assumption or approach is likely to change the total benefit estimate by less than five percent, the Project Team assigns a classification of “probably minor.”		

TABLE A-3. KEY UNCERTAINTIES ASSOCIATED WITH AIR QUALITY MODELING

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS	LIKELY SIGNIFICANCE RELATIVE TO KEY UNCERTAINTIES ON NET BENEFITS ESTIMATE*
PM_{10} and $PM_{2.5}$ concentrations in the East (RADM domain) are based exclusively on changes in the concentrations of sulfate and nitrate particles, omitting the effect of anticipated reductions in organic or primary particulate fractions.	Underestimate	Potentially major. Nitrates and sulfates constitute major components of PM, especially $PM_{2.5}$, in most of the RADM domain and changes in nitrates and sulfates may serve as a reasonable approximation of changes in total PM_{10} and total $PM_{2.5}$. Of the other components, primary crustal particulate emissions are not expected to change between scenarios; primary organic carbon particulate emissions are expected to change, but an important unknown fraction of the organic PM is from biogenic emissions, and biogenic emissions are not expected to change between scenarios. If the underestimation is major, it is likely the result of not capturing reductions in motor vehicle primary elemental carbon and organic carbon particulate emissions.
The number of $PM_{2.5}$ ambient concentration monitors throughout the U.S. is limited. As a result, cross estimation of $PM_{2.5}$ concentrations from PM_{10} (or TSP) data was necessary in order to complete the “monitor-level” observational dataset used in the calculation of air quality profiles.	Unable to determine based on the current information.	Potentially major. $PM_{2.5}$ exposure is linked to mortality, and avoided mortality constitutes a large portion of overall CAAA benefits. Cross estimation of $PM_{2.5}$, however, is based on studies that account for seasonal and geographic variability in size and species composition of particulate matter. Also, results are aggregated to the annual level, improving the accuracy of cross estimation.
Use of separate air quality models for individual pollutants and for different geographic regions does not allow for a fully integrated analysis of pollutants and their interactions.	Unable to determine based on current information	Potentially major. There are uncertainties introduced by different air quality models operating at different scales for different pollutants. Interaction is expected to be most significant for PM estimates. However, important oxidant interactions are represented in all PM models and the models are being used as designed. The greatest likelihood of error in this case is for the summer period in areas with NO_x inhibition of ambient ozone (e.g., Los Angeles).

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS	LIKELY SIGNIFICANCE RELATIVE TO KEY UNCERTAINTIES ON NET BENEFITS ESTIMATE*
Future-year adjustment factors for seasonal or annual monitoring data are based on model results for a limited number of simulation days.	Overall, unable to determine based on current information	Probably minor. RADM/RPM and REMSAD PM modeling simulation periods represent all four seasons and characterize the full seasonal distribution. Potential overestimation of ozone, due to reliance on summertime episodes characterized by high ozone levels and applied to the May-September ozone season, is mitigated by longer simulation periods, which contain both high and low ozone days. Also, underestimation of UAM-V western and UAM-IV Los Angeles ozone concentrations (see below) may help offset the potential bias associated with this uncertainty.
Comparison of modeled and observed concentrations indicates that ozone concentrations in the western states were somewhat underpredicted by the UAM-V model, and ozone concentrations in the Los Angeles area were underestimated by the UAM-IV model.	Unable to determine based on current information	Probably minor. Because model results are used in a relative sense (i.e., to develop adjustment factors for monitor data) the tendency for UAM-V or UAM to underestimate absolute ozone concentrations would be unlikely to affect overall results. To the extent that the model is not accurately estimating the relative changes in ozone concentrations across regulatory scenarios, the effect could be greater.
Ozone modeling in the eastern U.S. relies on a relatively coarse 12 km grid, suggesting NO_x inhibition of ambient ozone levels may be under represented in some eastern urban areas. Coarse grid may affect both model performance and response to emissions changes.	Unable to determine based on current information	Probably minor. Though potentially major for eastern ozone results in those cities with known NO_x inhibition, ozone benefits contribute only minimally to net benefit projections in this study. Grid size affects chemistry, transport, and diffusion processes which in turn determine the response to changes in emissions, and may also affect the relative benefits of low-elevation versus high-stack controls. However, the approach is consistent with current state-of-the-art for regional-scale ozone modeling.

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS	LIKELY SIGNIFICANCE RELATIVE TO KEY UNCERTAINTIES ON NET BENEFITS ESTIMATE*
UAM-V modeling of ozone in the western U.S. uses a coarser grid than the eastern UAM-V (OTAG) or UAM-IV models, limiting the resolution of ozone predictions in the West.	Unable to determine based on current information	Probably minor. Also, probably minor for ozone results. Grid cell-specific adjustment factors for monitors are less precise for the west and may not capture local fluctuations. However, exposure tends to be lower in the predominantly non-urban west, and models with finer grids have been applied to three key population centers with significant ozone concentrations. May result in underestimation of benefits in the large urban areas not specifically modeled (e.g., Denver, Seattle) with finer grid.
Emissions estimated at the county level (e.g., area source and motor vehicle NO_x and VOC emissions) are spatially and temporally allocated based on land use, population, and other surrogate indicators of emissions activity. Uncertainty and error are introduced to the extent that area source emissions are not perfectly spatially or temporally correlated with these indicators.	Unable to determine based on current information	Probably minor. Potentially major for estimation of ozone, which depends largely on VOC and NO_x emissions; however, ozone benefits contribute only minimally to net benefit projections in this study.
The REMSAD model underpredicted western PM concentrations during fall and winter simulation periods.	Unable to determine based on current information	Probably minor. Because model results are used in a relative sense (i.e., to develop adjustment factors for monitor data) REMSAD's underestimation of absolute PM concentrations would be unlikely to significantly affect overall results. To the extent that the model is not accurately estimating the relative changes in PM concentrations across regulatory scenarios, or the individual PM components (e.g., sulfates, primary emissions) do not vary uniformly across seasons, the affect could be greater.

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS	LIKELY SIGNIFICANCE RELATIVE TO KEY UNCERTAINTIES ON NET BENEFITS ESTIMATE*
Lack of model coverage for acid deposition in Western states.	Underestimate	Probably minor. Because acid deposition tends to be a more significant problem in the eastern U.S. and acid deposition reduction contributes only minimally to net monetized benefits, the monetized benefits of reduced acid deposition in the western states would be unlikely to significantly alter the total estimate of monetized benefits.
Uncertainties in biogenic emissions inputs increase uncertainty in the AQM estimates.	Unable to determine based on current information	Probably minor. Potentially major impacts for ozone outputs, but ozone benefits contribute only minimally to net benefit projects in this study. Uncertainties in biogenics may be as large as a factor of 2 to 3. These biogenic inputs affect the emissions-based VOC/NO_x ratio and, therefore, potentially affect the response of the modeling system to emissions changes.
* The classification of each potential source of error reflects the best judgment of the section 812 Project Team. The Project Team assigns a classification of "potentially major" if a plausible alternative assumption or approach could influence the overall monetary benefit estimate by approximately five percent or more; if an alternative assumption or approach is likely to change the total benefit estimate by less than five percent, the Project Team assigns a classification of "probably minor."		

TABLE A-4. KEY UNCERTAINTIES ASSOCIATED WITH HUMAN HEALTH EFFECTS MODELING

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS ESTIMATE	LIKELY SIGNIFICANCE RELATIVE TO KEY UNCERTAINTIES IN NET BENEFIT ESTIMATE*
Application of C-R relationships only to those subpopulations matching the original study population.	Underestimate	Potentially major. The C-R functions for several health endpoints (including PM-related premature mortality) were applied only to subgroups of the U.S. underestimate the whole population benefits of reductions in pollutant exposures. In addition, the demographics of the study population in the Pope et al. study (largely white and middle class) may result in an underestimate of PM-related mortality, because the effects of PM tend to be significantly greater among groups of lower socioeconomic status.
No quantification of health effects associated with exposure to air toxics.	Underestimate	Potential major. According to EPA criteria, over 100 air toxics are known or suspected carcinogens, and many air toxics are also associated with adverse health effects such as neurotoxicity, reproductive toxicity, and developmental toxicity. Unfortunately, current data and methods are insufficient to develop (and value) quantitative estimates of the health effects of these pollutants.
Use of long-term global warming estimates in Title VI analysis that show more severe warming than is now generally anticipated.	Overestimate (for Title VI estimate only)	Potentially major. Global warming can accelerate the pace of stratospheric ozone recovery; if warming is less severe than anticipated at the time the Title VI analyses were conducted, the modeled pace of ozone recovery may be overestimated, suggesting benefits of the program could be delayed, perhaps by many years. The magnitude of estimated Title VI benefits suggests that the impact of delaying benefits could be major.

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS ESTIMATE	LIKELY SIGNIFICANCE RELATIVE TO KEY UNCERTAINTIES IN NET BENEFIT ESTIMATE*
The quantitative analysis of Title VI (see next section) does not account for potential increases in averting behavior (i.e., people's efforts to protect themselves from UV-b radiation).	Unable to determine based on current information	Potentially major. Murdoch and Thayer (1990) estimate that the cost-of-illness estimates for nonmelanoma skin cancer cases between 2000 and 2050 may be almost twice the estimated cost of averting behavior (application of sunscreen). Our Title VI analysis relies on epidemiological studies, which incorporate averting behavior as currently practiced. Omission of future increases in averting behavior, however, may overstate the benefits of reduced emissions of ozone-depleting chemicals. Benefits could be understated if individuals alter their behaviors in ways that could increase exposure or risk (e.g., sunbathing more frequently). A recent European study by Autier et al. (1999) found that the use of high sun protection factor (SPF) sun screen is associated with increased frequency and duration of sun exposure.
Analysis assumes a causal relationship between PM exposure and premature mortality based on strong epidemiological evidence of a PM/mortality association. However, epidemiological evidence along cannot establish this causal link.	Unable to determine based on current information	Potentially major. A basic underpinning of this analysis, this assumption is critical to the estimation of health benefits. However, the assumption of causality is suggested by the epidemiologic evidence and is consistent with current practice in the development of a best estimate of air pollution-related health benefits. At this time, we can identify no basis to support a conclusion that such an assumption results in a known or suspected overestimation bias.

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS ESTIMATE	LIKELY SIGNIFICANCE RELATIVE TO KEY UNCERTAINTIES IN NET BENEFIT ESTIMATE*
Across-study variance/application of regionally derived C-R estimates to entire U.S.	Unable to determine based on current information	Potentially major. The differences in the expected changes in health effects calculated using different underlying studies can be large. If differences reflect real regional variation in the PM/mortality relationship, applying individual C-R functions throughout the U.S. could result in considerable uncertainty in health effect estimates.
Estimate of non-melanoma skin cancer mortality resulting from reductions in stratospheric ozone is calculated indirectly, by assuming the mortality rate is a fixed percentage of non-melanoma incidence.	Unable to determine based on current information	Potentially major. New data on the death rate for non-melanoma skin cancer may significantly influence the Title VI mortality estimate. Some preliminary estimates suggest that this estimate may need to be adjusted downward.
The baseline incidence estimate of chronic bronchitis based on Abbey et al. (1995) excluded 47 percent of the cases reported in that study because those reported "cases" experienced a reversal of symptoms during the study period. These "reversals" may constitute acute bronchitis cases that are not included in the acute bronchitis analysis (based on Dockery et al. 1996).	Underestimate	Probably minor. The relative contribution of acute bronchitis cases to the overall benefits estimate is small compared to other health benefits such as avoided mortality and avoided chronic bronchitis.
CAAA fugitive dust controls implemented in PM non-attainment areas would reduce lead exposures by reducing the re-entrainment of lead particles emitted prior to 1990. This analysis does not estimate these benefits.	Underestimate	Probably minor. While the health and economic benefits of reducing lead exposure can be substantial (e.g., see section 812 Retrospective Study Report to Congress), most additional fugitive dust controls implemented under the Post-CAAA scenario (e.g., unpaved road dust suppression, agricultural tilling controls, etc.) tend to be applied in relatively low population areas.

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS ESTIMATE	LIKELY SIGNIFICANCE RELATIVE TO KEY UNCERTAINTIES IN NET BENEFIT ESTIMATE*
Exclusion of C-R functions from short-term exposure studies in PM mortality calculations.	Underestimate	Probably minor. Long-term PM exposure studies may be able to capture some of the impact of short-term peak exposure one mortality; however, the extent of overlap between the two study types is unclear.
Age-specific C-R functions for PM related premature mortality not reported by Pope et al. (1995). Estimation of the degree of life-shortening associated with PM-related mortality used a single C-R function for all applicable age groups.	Unable to determine based on current information	Unknown, possibly major when using a value of life year's approach. Varying the estimate of degree of prematurity has no effect on the aggregate benefit estimate when a value of statistical life approach is used, since all incidences of premature mortality are valued equally. Under the alternative approach based on valuing individual life-years, the influence of alternative values for number of average life years lost may be significant.
Assumption that PM-related mortality occurs over a period of five-years following the critical PM exposure. Analysis assumes that 25 percent of deaths occur in year one, 25 percent in year two, and 16.7 percent in each of the remaining three years.	Unable to determine based on current information	Probably minor. If the analysis underestimates the lag period, benefits will be overestimated, and vice-versa. However, available epidemiological studies do not provide evidence of the existence or potential magnitude of a lag between exposure and incidence. Thus, an underestimate of the lag seems unlikely. If the assumed lag structure is an overestimate, even if benefits are fully discounted from the future year of death, application of reasonable discount rates over this period would not significantly alter the monetized benefit estimate.

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS ESTIMATE	LIKELY SIGNIFICANCE RELATIVE TO KEY UNCERTAINTIES IN NET BENEFIT ESTIMATE*
Extrapolation of criteria pollutant concentrations to populations distant from monitors.	Unable to determine based on current information	Probably minor. Extrapolation method is most accurate in areas where monitor density is high. Monitor density tends to be highest in areas with high criteria pollutant exposures; thus most of this uncertainty affects low exposure areas where benefits are likely to be low. In addition, an enhanced extrapolation method incorporation modeling results is used for areas fare (> 50 km) from a monitor.
Exposure analysis in areas beyond 50 km is based on a new technique that relies on the direct use of air quality modeling results in combination with adjusted monitor data.	Unable to determine based on current information	Probably minor. The new technique is used for less than 10 percent of the country for PM exposure, and less than 15 percent for ozone. The approach we use should be more accurate than the alternative approach of linear interpolation over long distances. The new method nonetheless requires further testing against monitor data to access its accuracy.
Pope et al. (1995) study did not include pollutants other than PM.	Unable to determine based on current information	Probably minor. If ozone and other criteria pollutants correlated with PM contribute to mortality, that effect may be captured in the PM estimate. Thus, PM is essentially used as a surrogate for a mix of pollutants. This uncertainty does make it difficult to disaggregate avoided mortality benefits by pollutant, however other studies (besides Pope) suggest that PM is the dominant factor in premature mortality.
* The classification of each potential source of error reflects the best judgment of the section 812 Project Team. The Project Team assigns a classification of "potentially major" if a plausible alternative assumption or approach could influence the overall monetary benefit estimate by approximately five percent or more; if an alternative assumption or approach is likely to change the total benefit estimate by less than five percent, the Project Team assigns a classification of "probably minor."		

TABLE A-5. KEY UNCERTAINTIES ASSOCIATED WITH ECOLOGICAL EFFECTS ESTIMATION

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS	LIKELY SIGNIFICANCE RELATIVE TO KEY UNCERTAINTIES ON NET BENEFITS ESTIMATE*
Incomplete coverage of ecological effects identified in existing literature, including the inability to adequately discern the role of air pollution in multiple stressor effects on ecosystems.	Underestimate	Potentially major. The extent of unquantified and unmonetized benefits is largely unknown, but the available evidence suggests the impact of air pollutants on ecological systems may be widespread and significant. At the same time, it is possible that a complete quantification of effects might yield economic valuation results that remain small in comparison to the total magnitude of health benefits.
Omission of the effects of nitrogen deposition as a nutrient with beneficial effects.	Overestimate	Probably minor. Although nitrogen does have beneficial effects as a nutrient in a wide range of ecological systems, nitrogen in excess also has significant and in some cases persistent detrimental effects that are also not adequately reflected in the analysis.
Incomplete assessment of long-term bioaccumulative and persistent effects of air pollutants.	Underestimate	Potentially major. Little is currently known about the longer-term effects associated with the accumulation of toxins in ecosystems. But what is known suggests the potential for major impacts. Future research into the potential for threshold effects is necessary to establish the ultimate significance of this factor.
The PnET II modeling of the effects of ozone on timber yields relies on a simplified mechanism of response (i.e., changes in net primary productivity).	Overestimate	Probably minor. Existing evidence suggests that the growth changes PnET II projects are relatively large, however none of the currently available points of comparison fully address such issues as the impact of stand-level competition, and the net primary productivity results are within the range of results of other studies of environmental and anthropogenic stressors.

* The classification of each potential source of error reflects the best judgment of the section 812 Project Team. The Project Team assigns a classification of “potentially major” if a plausible alternative assumption or approach could influence the overall monetary benefit estimate by approximately five percent or more; if an alternative assumption or approach is likely to change the total benefit estimate by less than five percent, the Project Team assigns a classification of “probably minor.”

TABLE A-6. SUMMARY OF KEY SOURCES OF UNCERTAINTY AND THEIR IMPACT ON COSTS AND BENEFITS

SOURCE OF UNCERTAINTY	DESCRIPTION OF ALTERNATIVE PARAMETER INPUTS	IMPACT ON ANNUAL ESTIMATES IN 2010	
		COSTS	BENEFITS
Measurement error and uncertainty in the physical effects and economic valuation steps.	Use a range of input assumptions to reflect statistical measurement uncertainty in concentration-response functions, modeling of physical effects, and estimation of economic values. Most important input parameters are value of statistical life and estimated relationship between particulate matter and premature mortality (see Chapters 5, 6, and 7).	None	For Titles I through V, effect of the use of alternative input assumptions ranges from \$84 billion decrease (5th percentile) to a \$160 billion increase (95th percentile).
Measurement error and uncertainty in direct cost inputs	Use alternative assumptions for key input parameters for six of the highest cost provisions. Conduct sensitivity tests for each provision separately (see Chapter 3, pages 30 to 32). As discussed in Chapter 3 and in this chapter, aggregation of provision-specific results would be inappropriate.	High estimates for some provisions are \$1 billion higher than primary estimate. Low estimates are as much as \$2 billion below primary estimates.	None
Value of statistical life-based estimates do not reflect age at death.	Use estimates of the incremental number of life-years lost from exposure to ambient PM and a value of statistical life-year as opposed to measuring number of lives lost and a value of statistical life (see Chapters 5 and 6).	None	Decrease by \$47 billion
Basis of estimate of avoided mortality from PM exposure	The Dockery et al. study provides an alternative estimate of the long-term relationship between chronic PM exposure and mortality (see Chapter 5).	None	Increase by \$100 to \$150 billion

SOURCE OF UNCERTAINTY	DESCRIPTION OF ALTERNATIVE PARAMETER INPUTS	IMPACT ON ANNUAL ESTIMATES IN 2010	
		COSTS	BENEFITS
Uncertainties in title VI health benefits analysis	Major uncertainties include: estimating fatal cancer cases resulting from UV-b exposure; not accounting for future averting behavior; and not accounting for future improvements in the early detection and treatment of melanoma (see Table 5—6).	None	Not quantified, but net effect is probably that benefits estimates are too low.
Omission of potentially important benefits categories from primary estimates.	Non-quantified categories of impacts summarized in Chapters 5 and 7. Quantified but omitted categories include household soiling, nitrogen deposition, and residential viability (see Chapter 7).	None	Increase by at least $8 billion, (does not reflect unquantified categories).

APPENDIX B | UNCERTAINTY ANALYSIS OF THE INTEGRATED AIR QUALITY MODELING SYSTEM

March 30, 2009

To: James Neumann, Industrial Economics, Inc. STI-908026.02-3537-TM

From: Neil Wheeler and Kenneth Craig

Re: Uncertainty Analysis of the Integrated Air Quality Modeling System for use in the U.S. Environmental Protection Agency's Section 812 Second Prospective Analysis

Under Section 812 of the Clean Air Act Amendments (CAAA), the U.S. Environmental Protection Agency (EPA) is requested to periodically conduct and submit to Congress a report on economic benefits and costs of all provisions of the Act and its Amendments. The EPA delivered the first of these reports, a retrospective analysis covering provisions of the original Clean Air Act during the period 1970-1990, in 1997, and the second report, a prospective analysis covering provisions of the CAAA during the period 1990-2010, in 1999.

The EPA is currently working on the third report to be developed under Section 812. This "Second Prospective Analysis" will estimate benefits and costs for provisions of the Amendments as they are expected to be implemented during the period 1990-2020.

In September 2004, Sonoma Technology, Inc. (STI) completed a literature review that summarized much of the existing uncertainty literature and assessed the possible application of existing approaches to the Second Prospective Analysis for estimating the uncertainties in the integrated air quality modeling system (IAQMS), which includes the emissions, meteorological, and air quality models.[148]

This memorandum covers the two deliverables for Work Assignment 4-15 as revised on October 15, 2008. The first deliverable is an updated literature review of uncertainties in IAQMSs and methods for quantifying them (Section 1) and the evaluation and overall reliability of IAQMSs (Section 2). The second deliverable is a discussion of the IAQMS used in the Second Prospective Analysis and a draft table that summarizes key uncertainties in the IAQMS, potential sources of error, potential biases for the net benefits estimate, and the likely significance relative to key uncertainties in net benefit estimate (Section 3). References cited throughout this document are provided in Section 4.

[148] See September 30, 2004 memorandum to Nona Smoke and James DeMocker, EPA/OAR/OPAR, from Neil Wheeler and Kiren Baum, Sonoma Technology, Inc., "Response to Council Comments on the May 2003 Draft Analytical Plan for the Section 812 Second Prospective – Options for Uncertainty Analysis for Emissions and Air Quality Analyses".

UNCERTAINTIES IN THE IAQMS

Sources of Uncertainty

Uncertainty in estimated values for future air quality arises from at least three sources: (1) inherent or stochastic variability in the observations; (2) errors in model physics and chemistry assumptions; and (3) errors caused by uncertainties in model input variables. For prospective analyses, we need to focus on uncertainty in the context of model response to future-year emissions. For example, an air quality model (AQM) may be very sensitive to a particular input without affecting its response to emission changes. Alternatively, an AQM may show little sensitivity to an input under current conditions (e.g., boundary conditions) but become increasingly sensitive to that input in future years as anthropogenic emissions are reduced.

Measurement Uncertainty

While measurement uncertainty is less important when using relative reduction factors (RRFs) and linear cost-response functions, it can affect the ability to evaluate model performance and gain confidence that a model is getting the right answer for the right reason. For gases, instruments can be calibrated using gases of known concentrations, and the uncertainty in the measurement is reasonably well known. However, this is not the case for PM. Uncertainties in PM mass and speciation can be significant, which limits our ability to critically evaluate model performance and reduce uncertainty in model simulations.

Hogrefe et al. (2000) developed an approach to gain insight into the distribution of future air quality predictions attributable to variability in currently observed air quality at a given location. The procedure is to fit a theoretical statistical distribution to the tail of a set of daily observations at a monitoring site (e.g., over a three-year period) and compute a design value consistent with the form of the National Ambient Air Quality Standards (NAAQS). The next step is to perform a bootstrapping operation several hundred times to obtain different sets of air quality data. For each instance, a design value is determined from the resulting data. The result is a distribution of current design values, which can be translated into a distribution of future air quality estimates using the RRF approach recommended in EPA guidance. While work so far has focused on the 1-hr and 8-hr NAAQS for ozone, it may be possible to apply the methodology to PM-related applications.

Model Uncertainty

Emissions, meteorological, and air quality models are mathematical representations of the physical world, and as such, have inherent uncertainties associated with their formulation, assumptions, and implementation. Some of the uncertainties are due to the limitations of our scientific knowledge. Other uncertainties are a result of simplifications or approximations needed to make the model practical. At the present time, we do not see a way to completely quantify uncertainty caused by inherent limitations in a model. However, methods and a body of research are available to help us understand the importance of uncertainty in individual model components. We can also reduce uncertainty by using models whose scientific basis is fully and satisfactorily explained in its accompanying documentation.

In some cases, it is necessary to use a simplified "engineering" or "reduced-form" version of a model. Uncertainty inherent in such results may be reduced if it has been shown that the engineering and more complete versions of a model produce similar results under the conditions that are of greatest interest for a particular application.

Input Uncertainty

The best-formulated and least uncertain models are only as good as their inputs. Model input uncertainty has been explored extensively in past decades and has driven research to improve these model inputs. In some cases, these inputs are based on measurements, which may be available only at limited temporal or spatial resolutions. In other cases, the input for one model may be the output of another model (i.e., the use of a mobile source emissions model to provide input to an AQM).

Methods for Assessing the Effects of Uncertainty

Sensitivity analysis is the most widely used method for assessing the effects of uncertainty on future-year air quality outcomes. Process analysis has been used in more recent AQM applications to identify those processes in the AQM that contribute the most to predicted pollutant concentrations and, thus, may be most affected by uncertainty. These methods and their use are discussed in greater detail below.

Sensitivity Analysis

The response of AQM predictions to changes of input parameters or model options can provide valuable information about uncertainties in model predictions. Such information can be obtained by sensitivity analysis, the systematic calculation of sensitivity coefficients, to quantitatively measure these dependencies. Basic sensitivity analysis may involve perturbing input parameters or model options one at a time or in combinations.

Beck et al. (1997) provide an overview of evaluations and uncertainties of environmental models, with emphasis on water quality models. They stress the need to specify a hypothesis or question to be answered by the model, and describe three alternatives to basic sensitivity analysis: (1) brute-force MC uncertainty analysis; (2) response surface evaluation; and (3) first-order error analysis, which is sometimes called sensitivity or "small perturbation" analysis. Each technique is discussed below.

Basic Sensitivity Analysis

Because of its ease of use and interpretation, there exist many examples of basic sensitivity analysis applied to AQMs. For example, Seigneur et al. (1981) estimated the sensitivities of an urban model to variations in input data. Winner et al. (1995) and Dabdub et al. (1999) showed that ozone predictions are especially sensitive to the inflow boundary conditions in Los Angeles and the San Joaquin Valley, respectively. Hass et al. (1997) carried out a sensitivity study of four European long-range transport and dispersion models, finding factors of 2 to 3 differences in the sensitivities of the different models to variations in emissions. Our review of these sensitivity studies suggests that the results are applicable only to a narrow range of conditions associated with the specific scenario. Because photochemical processes are often non-linear, the magnitude and even the sign of the sensitivity coefficients may vary as the scenario varies.

While meteorological parameters are undoubtedly important in photochemical grid models, it is not easy to decide how to account for variations in meteorology, especially wind speed and direction. The problem is that it is necessary for the wind field to always satisfy mass-continuity, so that it is not correct to simply randomly vary the winds in each grid square of the model. Photochemical grid models make use of meteorological preprocessors, which may adjust the wind fields so they are mass-consistent. Hanna et al. (1998) avoided this problem by assuming that the perturbations in wind speed and direction applied uniformly across all grid squares. Schere and Coates (1992) suggested a more elegant (and time-consuming) method of accounting for uncertainties or variations in winds. Bergin et al. (1999) attacked the problem by generating a small number of alternate wind fields based on systematically "withdrawing" data from the meteorological preprocessor. This method is a useful first estimate but will underestimate the total uncertainty because of the limited number of runs and the failure to account for the full range of wind uncertainty.

Meteorologists have accounted for variability in weather forecasts by applying the "ensemble" method in which several forecast models (i.e., an ensemble) are run for the same scenario, and the best-guess forecast is assumed to be given by the mean of the several forecasts. These methods have been applied to air quality models by Straume et al. (1998), who showed that the ensemble method produced improved forecasts of tracer concentrations for the long-range ETEX tracer experiment in Europe. It is implied that the uncertainty would be given by the variability of the forecasts. These methods have also been extended to regulatory air quality modeling by using and evaluating alternative AQMs. For example, Ozone Transport Assessment Group (1997) modeling used multiple meteorological models (SAIMM and RAMS) and multiple AQMs (UAM-V and CAMx) for some episodes. However, it is clear that the full range of possible input conditions can not be covered by these ensemble methods.

The EPA guidance documents on attainment demonstrations (U.S. Environmental Protection Agency, 1999, 2001) identify three sensitivity tests that may be useful for assessing uncertainty in AQM predictions. The first of these, which has been proposed by Reynolds et al., (1996), is to prepare "alternative base-case" emission estimates, reflecting reasonable alternative assumptions about current emissions that lead to comparable or better model performance. A second test is to assume alternative (reasonable) growth assumptions. This could reflect using differing growth rates or placement of new sources in different, equally probable locations. Combinations of these first two tests are also possible. A third test involves simulating a future-year case with an alternative grid resolution or with different (reasonable) meteorological assumptions. For example, due to resource constraints, it might be necessary to perform modeling using a grid with 36-km grid cells (horizontal dimension). Differences in projected air quality obtained with a grid having 12-km or 4-km cells could then be evaluated.

The EPA guidance documents on modeling for attainment demonstrations were influenced by earlier guidance developed at the California Air Resources Board (CARB), which specifically addressed uncertainty (DaMassa, 1992). CARB applied this guidance in a series of uncertainty analyses to support the development of California's State Implementation Plans (SIPs). This program included analyses of uncertainty associated with future-year boundary conditions (Wagner and Wheeler, 1988), meteorology (Wagner and Wheeler, 1989; Wheeler, 1992), emission inventory bias (Wagner et al., 1992), horizontal advection solvers (Odman et al., 1996), chemical mechanisms (Whitten and Killus, 1998), and photolysis rates (Vuilleumier et al., 2000).

Monte Carlo Uncertainty Analysis

Monte Carlo (MC) methods are the most widely used means for uncertainty analysis. These methods involve random sampling from the distribution of inputs and successive model runs until a statistically significant distribution of outputs is obtained. There has been a rapid growth in the use of MC uncertainty analysis with photochemical AQMs in recent years. This "brute-force" method is computer-intensive because it requires 50 to 100 or more model runs for each base-year and future emission scenario. However, because of the exponential growth of computer speed and storage, it is now possible to carry out MC runs with a complex photochemical grid model applied to large domain. This method has been widely used in other environmental fields (e.g., water pollution modeling), as described in the reviews by International Atomic Energy Agency (IAEA) (1989), National Council on Radiation Protection and Measurements (NCRP) (1996), and Beck et al. (1997).

One of the first applications of MC uncertainty analysis to photochemistry was the study of relationships between stratospheric ozone and chlorine reported by Solarski et al. (1978). Alcamo and Bartnicki (1987) used MC methods to study the uncertainties in sulfur deposition predicted by the EMEF-W model in Europe. They found that it is more important to specify the width (i.e., the standard deviation) rather than the shape of the probability density function of the input variables. Irwin et al. (1987) performed an MC uncertainty analysis to estimate error bounds from the output of a Gaussian dispersion model. Uncertainties in wind speed, standard deviation of vertical and lateral wind direction fluctuations, and plume rise were propagated through the modeling system. It was found that the error bounds for the maximum concentration could be double that of the error bounds for the input parameters. This is one of the earlier papers on using uncertainty analysis on a dispersion model. Gao et al. (1996) applied MC uncertainty analysis to the chemical rate parameters. Deuel et al. (1998) studied the uncertainties of the UAM-V model using MC methods; however, the uncertainty ranges that they assumed for the input variables (vertical resolution, vertical diffusivity, plume-in-grid method, land-use, chemical reaction rates, and emissions) were a third or less than those recommended by the experts in the studies by Hanna et al. (1998, 2001). Bergin et al. (1999) applied MC methods with Latin Hypercube Sampling (LHS) to a Lagrangian photochemical AQM (i.e., not a grid model) in Southern California. They accounted for meteorological variability by using several solutions of a mass-consistent wind model, run with random data-withholding assumptions.

Frey (1992) discusses the decision process followed in applications of MC uncertainty analysis, stressing the importance of good estimates of input data uncertainties. Conover (1971) provides guidance concerning the computation of statistical tolerance limits from a simple random sample. Bergin et al. (1999) discuss the use of LHS, which they believe provides a better coverage of the data distribution than Simple Random Sampling (SRS). However, the advantage of LHS comes with a price—only with SRS can the confidence in the results be interpreted through statistical tolerance limits.

From a practical standpoint, Hanna et al. (2001) demonstrated that MC methods could be applied to larger photochemical modeling studies (i.e., OTAG) by performing 100 simulations each for a base-case and three emission reduction scenarios. Hanna and Davis (2002) evaluated the UAM-V photochemical grid model by examining probability density functions of the variations in modeled ozone concentrations. The probability density functions are generated from 100 MC uncertainty simulations based on uncertainties in model input variables.

Houyoux et al. (2003) simplified the use of AQMs for assessing emission inventory uncertainties by generating multiple realizations of model-ready emissions with the Sparse Matrix Operator Kernel Emissions (SMOKE) processing system (Coats and Houyoux, 1996) by modifying SMOKE to accept parametric and empirical probability distributions to describe the uncertainty about them. This approach allows emissions modelers to assign uncertainty information about an existing inventory without having to change the actual inventory files. The same inventories can be used for both deterministic (i.e., without uncertainty) modeling and stochastic modeling (i.e., with uncertainty), and the type of modeling that is performed depends only on the presence of the additional inventory uncertainty file.

Wang et al. (2000) estimated uncertainties in incremental reactivities for the SAPRC-97 chemical mechanism, with an emphasis on aromatic mechanism parameters, using Monte Carlo analysis with LHS. Rodriguez and Dadbub (2003) performed an MC uncertainty and sensitivity analysis of the Caltech Atmospheric Chemistry Mechanism (CACM), with an emphasis placed on secondary organic aerosol. Uncertainties were propagated through box model simulations.

Hanna et al. (2006) performed a Monte Carlo uncertainty analysis with ISCST3 and AERMOD to study uncertainties in annual average benzene and 1,3-butadiene concentrations in the Houston Ship Channel area caused by uncertainties in meteorological inputs, emissions inputs, and dispersion model parameters.

Martien et al (2006) developed a continuous adjoint sensitivity analysis procedure for a three-dimensional photochemical model to determine the sensitivity of a small number of model responses to many parameters. Menut (2003) also applied an adjoint sensitivity method for a photochemical sensitivity analysis.

Deguillaume et al. (2007) applied a Bayesian Monte Carlo uncertainty analysis to a regional-scale inverse emission modeling study to estimate emission uncertainty in the Ile-de-France region. Deguillaume et al. (2008) applied a Bayesian Monte Carlo analysis to evaluate model uncertainty in ozone production and its sensitivity to emission changes in the CHIMERE model for the Ile-de-France region during the 1998 and 1999 summer seasons. The use of observations to constrain the analysis reduced uncertainty of predicted ozone concentrations.

Response Surface Analysis

Forms of response surface approximations have been used in a variety of scientific, engineering, and economic modeling applications, including groundwater flow using the Stochastic Response Surface Method (SRSM) (Balakrishnan et al., 2003, 2005); radiative forcing by anthropogenic sulfate aerosol Probability Collocation Method (PCM) (Pan et al., 1998); climate change using the PCM (Webster and Sokolov, 2000; Webster et al., 2006), and soil moisture in the NOAA Land Surface Model (Hossain et al., 2004).

Response surface models have been used in the air quality field for the past decade. Calbo et al. (1998) used PCM to develop a parameterization consisting of a set of analytical expressions that approximate the predictions by the CIT Urban Airshed Model. Parameterization development was the ultimate focus of this work, but the authors mentioned that their parameterization was applicable to detailed uncertainty and sensitivity analysis. Isukapalli et al., (1998) applies SRSM to propagate uncertainty through the Reactive Plume Model (RPM-IV). The results agreed closely with those of traditional MC and LHS methods, while significantly reducing the required number of model simulations. Isukapalli et al. (2000) coupled SRSM to the Automatic Differentiation of FORTRAN (ADIFOR) to propagate uncertainty through the Reactive Plume Model (RPM-IV). EPA has developed and used an RSM based on the Community Multiscale Air Quality (CMAQ) model to develop emissions control scenarios in support of the Regulatory Impact Assessment for the $PM_{2.5}$ NAAQS (U.S. Environmental Protection Agency, 2006b).

The response surface method is at the other extreme from simple one-at-a-time sensitivity studies. This method (Tatang et al., 1997) attempts to fit orthogonal polynomials to the input conditions and the predictions of numerical geophysical models. For this approach, it is necessary to run the models a sufficient number of times to have enough data to develop the response surfaces. It is claimed that 25 to 60 times fewer runs are needed than for a MC SRS exercise. However, in a Response Surface Model (RSM) pilot study, Hubbell (2003) reported that 144 REMSAD runs were required to characterize a second order polynomial surface to develop an RSM for $PM_{2.5}$.

Nevertheless, the response surface is a model of a model and, therefore, is susceptible to problems associated with scenarios outside of the range of parameters used to generate the data for deriving the model.

First-order Sensitivity Analysis

Sensitivity analysis has not been used as extensively as desired because of implementation complexity and computational limitations. As a result, the simple “brute-force” method has been used most frequently to determine model sensitivities, especially in multidimensional chemistry transport models. By this method, a separate simulation is required to calculate the effects of each parameter or emission rate in the model. However, this approach rapidly becomes impractical when a large number of sensitivity coefficients need to be computed.

A number of other approaches have been developed to calculate sensitivity coefficients. One method of reducing this effort is determining the equations governing the sensitivity coefficients and solving them directly. In this method, the sensitivity equations are derived from the model equations and solved simultaneously with the model equations. This method proved to be unstable and inefficient when applied to stiff equations found in many air quality problems (Dunker, 1984). Other techniques rely on Green’s function (Rabitz et al., 1983; Cho et al., 1987; Harley et al., 1997) or the adjoint method, in which the sensitivity coefficients are computed from integrals of the Green’s function of sensitivity equations derived from the model equations.

The automatic differentiation of Fortran (ADIFOR) technique (Bischof et al., 1992) automatically translates large FORTRAN codes to a subprogram that includes the original functions as well as those for the desired sensitivity coefficients. This method has been used in past studies for sensitivity analysis of the advection equation as used for atmospheric modeling (Hwang et al., 1997), and initial concentrations and reactions rates in photochemical models

(Carmichael et al., 1997). Because ADIFOR is designed for general-purpose sensitivity analysis, the expanded codes do not take advantage of the program structure and re-use of calculations. Also, computing some sensitivity coefficients, such as those with respect to the subdomain emissions or the boundary conditions, requires additional modifications that can be cumbersome.

Another approach for computing sensitivity coefficients is the decoupled direct method (DDM) (Dunker, 1981; 1984), in which the sensitivity equations are derived from the model equations, but solved separately. DDM does not share the instability problem found with the direct and adjoint methods. Furthermore, the implementation of this method is more straightforward than the coupled direct or adjoint methods because the sensitivity equations are linear, even though they are functions of concentrations. Therefore, the calculations of sensitivity coefficients are much less computationally demanding. Milford et al. (1992) and Seefeld and Stockwell (1999) also applied the DDM to study variations in chemical rate constants.

Another technique for sensitivity study is DDM-3D (decoupled direct method in three dimensions), which has been successfully implemented in the CIT, CAMx, and CMAQ photochemical AQMs. This approach is highly computation-efficient and capable of calculating a full set of model sensitivity in a three-dimensional domain. Yang et al. (1997) first implemented DDM in a three-dimensional photochemical model (now known as DDM-3D). This implementation was used to calculate first-order ozone sensitivities to dry deposition velocity, initial conditions, rate constants, and NO_x and VOC emissions for a 1987 South Coast ozone episode. DDM-3D was implemented into CAMx version 3.0.0 by Dunker et al. (2002) to calculate first-order ozone sensitivities with respect to emissions and boundary conditions for a 1995 Lake Michigan ozone episode.

Higher-order Sensitivity Analysis

First-order DDM sensitivity analysis is limited because it assumes linear responses to input changes. The use of the higher-order direct decoupled method (HDDM) and its higher-order coefficients allows DDM to be extended to study non-linear responses, and can be used to study the uncertainty of modeled sensitivities. Most studies that have implemented and tested HDDM have not specifically used the technique to examine uncertainty in pollutant response attributable to uncertainties in inputs.

Hakami et al. (2003) extended DDM-3D to calculate higher-order ozone sensitivities in the MAQSIP photochemical grid model for the 1990 SARMAP domain. HDDM was initially implemented for the CB-IV chemical mechanism, and later extended to the more complex SAPRC chemical mechanism (Hakami et al., 2004). HDDM was ported to CMAQ by Cohan et al. (2005) to CMAQ and applied to a 2001 ozone episode during the Fall Line Air Quality Study. Recently, DDM-3D was extended to calculate first-order sensitivities of $PM_{2.5}$ species in CMAQ (Napelenok et al. 2006).

Hakami et al. (2003) and Cohan et al. (2005) suggested that second-order sensitivity coefficients calculated from HDDM could be applied to quantitatively determine the uncertainty in pollutant sensitivity to uncertain photochemical model inputs. Cohan et al. (2005) used higher-order sensitivity coefficients from HDDM to illustrate how sensitivity and source apportionment estimates can be affected by uncertainty in emissions inventories. Jin et al. (2008) used the second-order sensitivity coefficients from HDDM in CMAQ to assess the influences of uncertainties in various model inputs. Uncertainties in NO_x and anthropogenic VOC emissions, and the rate coefficient for the OH + NO_2 termination reaction were found to have the greatest effect on first-order ozone responses to changes in NO_x emissions.

Though Jin et al. (2008) and Cohan et al. (2005) use HDDM to assess uncertainty, true quantitative uncertainty estimates of pollutant sensitivity to uncertain model inputs remain elusive. An attempt is currently underway to perform a quantitative uncertainty analysis using CMAQ-HDDM, with a Monte Carlo analysis as a post-processor (Digar et al. 2008).

Process Analysis

A technique called process analysis (PA) has been used to assess relative importance of various model assumptions as well as simulated physical and chemical phenomena contributing to an ozone concentration at a particular time and location (Jeffries, 1997; Jeffries et al., 1996; Jang et al., 1995; and Lo and Jeffries, 1997). Because models used to simulate ozone and secondary particulate matter are similar, process analysis should also be useful for addressing $PM_{2.5}$ issues. The technique works by breaking down a modeled simulation into a sequence of physical and chemical processes that lead to a predicted concentration at a given location and time and by tracking the contributions of those processes. PA has been implemented in CMAQ and CAMx but not REMSAD.

While PA requires a substantial amount of expertise to be interpreted to full advantage, useful insights are possible with less detailed analyses. PA takes advantage of numerical grid models that address physical and chemical factors affecting ozone in a sequential manner. For example, a typical sequence followed in a model for each time step might be (1) advection of $PM_{2.5}$ components and precursors present at the beginning of the time step, (2) $PM_{2.5}$ and precursor emissions added during the time step, (3) vertical diffusion of the advected material and fresh emissions, (4) estimated cloud cover and its effects on photolysis rates, (5) atmospheric chemistry involving advected and diffused material with fresh emissions, and (6) deposition of certain compounds. PA examines incremental effects on changes in component and/or $PM_{2.5}$ predictions from hour to hour attributable to each of the processes described above. In this way, one gets a sense of how important each process is as a contributor to predicted air quality at a specific time and location.

Quantifying Uncertainty in Model Inputs and Options

The first step in uncertainty analysis is to estimate the uncertainties in model input variables and options. Model options may include alternative techniques for solving model equations or alternative physical or chemical submodels. The two primary methods available for the Second Prospective Analysis are literature reviews and expert elicitation. For longer-term efforts in assessing uncertainty, these methods could be supplemented with specific applications of methods already discussed in the literature and in new research.

Literature Reviews

Past and current literature can provide estimates of uncertainties in model inputs based on measurement and sensitivity studies. Because models and measurements are constantly evolving, care must be taken to ensure that estimates of uncertainty in the literature are still valid.

Emission Inventories

Table 1 provides an overview of methods reviewed for the Emission Inventory Improvement Program (EIIP) in its final report on evaluating the uncertainty of emission estimates (Emission Inventory Improvement Program, 1996). While many of the studies cited are now out of date, the report provides a good summary of the methods available for quantifying uncertainty. NARSTO (2005) prepared an assessment of emission inventories across North America. NARSTO's findings on the relative confidence levels for emission inventories are summarized in Table 2.

Additional research has been performed to develop and demonstrate improved methods for quantifying uncertainty in emission inventories. A complete review of research on quantifying uncertainty in emission estimates was not possible within the scope of this work assignment. However, the following discussion provides many examples of the methods used and the results obtained.

In the area of mobile source emissions, Kini and Frey (1997) developed quantitative estimates of uncertainty associated with Mobile5b emission factor model estimates of light-duty gasoline-vehicle base emissions and speed-corrected emissions and found that the uncertainty in average emissions is often ±20% or more. Pollack et al. (1999) performed a similar study on California's EMFAC7G highway vehicle emission factor model. Frey et al. (1999) revisited the earlier analysis of Mobile5b emission factor estimates to include uncertainties associated with temperature corrections. Rhodes and Frey (1997) quantified variability and uncertainty in AP-42 emission factors using a bootstrap simulation method.

Table 1. Overview of methods for evaluating the uncertainty of emission estimates.

Method	Description	References
Qualitative Discussion	Sources of uncertainty are listed and discussed. General direction of bias and relative magnitude of imprecision are given if known.	Steiner et al., 1994
Subjective Data Quality Ratings	Subjective rankings based on professional judgment are assigned to each emission factor or parameter.	U.S. EPA, 1995 Saeger, 1994
Data Attribute Rating System (DARS)	Numerical values representing relative uncertainty are assigned through objective methods.	Beck et al., 1994
Expert Estimation Method	Emission distribution parameters (i.e., mean, standard deviation, and distribution type) are estimated by experts. Simple analytical and graphical techniques can then be used to estimate confidence limits from the assumed distributional data. In the Delphi method, expert judgment is used to estimate uncertainty directly.	Linstene and Turoff, 1975 SCAQMD, 1982 Horie, 1988 Horie and Shorpe, 1989
Propagation of Errors Method Direct Simulation Method	Emission parameter means and standard deviations are estimated using expert judgment, measurements, or other methods. Standard statistical techniques of error propagation typically based on Taylor's series expansions are then used to estimate the composite uncertainty.	Mangat et al., 1984 Benkovitz, 1985 Benkovitz and Oden, 1989 Balentine et al., 1994 Environment Canada, 1994
Direct Simulation Method	Monte Carlo, Latin hypercube, bootstrap (resampling), and other numerical methods are used to estimate directly the central value and confidence intervals of individual emission estimates. In the Monte Carlo method, expert judgment is used to estimate the values of the distribution parameters prior to performance of the Monte Carlo simulation. Other methods require no such assumptions.	Freeman et al., 1986 Iman and Helton, 1988 Oden and Benkovitz, 1990 Efron and Tibshirani, 1991 Environment Canada, 1994 Gatz and Smith, 1995a Gatz and Smith, 1995b
Direct or Indirect Measurement (Validation) Method	Direct or indirect field measurements of emissions are used to compute emissions and emission uncertainty directly. Methods include direct measurement such as stack sampling and indirect measurement such as tracer studies. These methods also provide data for validating emission estimates and emission models.	Pierson et al., 1990 Spellicy et al., 1992 Fujita et al., 1992 Peer et al., 1992 Mitchell et al., 1995

Method	Description	References
		Claiborn et al., 1995
Receptor Modeling (Source Apportionment) Method	Receptor modeling is an independent means to estimate the relative contribution of specific source types to observed air quality measurements. The method works best for nonreactive pollutants for which unique emission composition "fingerprints" exist for all significant source categories. The method provides a measure of the relative contribution of each source type but not absolute emission estimates.	Watson et al., 1984 Lowenthal et al., 1992 Chow et al., 1992 Scheff et al., 1995
Inverse Air Quality Modeling Method	Air quality simulation models are used in an inverse, iterative approach to estimate the emissions that would be required to produce the observed concentrations fields.	Hartley and Prinn, 1993 Chang et al., 1993 Chang et al., 1995 Mulholland and Seinfeld, 1995

Table 2. Estimated relative confidence levels of emission inventories.

Pollutants	Source	Canada	United States	Mexico
SO_2	Utilities	high	high	high
	Other point sources	medium	medium	low-medium
	On-road	medium	medium	low
	Nonroad mobile	low-medium	medium	low
	Stationary nonpoint	low	low	low
	Biogenic sources	low	low	low
	Other man-made sources (noncombustion)	low	low	low
NO_x	Utilities	medium-high	high	medium
	Other point sources	medium	medium	medium
	On-road	medium-high	medium-high	medium
	Nonroad mobile	medium	medium	low
	Stationary nonpoint	low	low	low
	Biogenic sources	low	low	low

Pollutants	Source	Canada	United States	Mexico
	Other man-made sources (noncombustion)	medium	medium	low
VOC	Utilities	medium-high	medium-high	medium
	Other point sources	low-medium	low-medium	medium
	On-road	low-medium	low-medium	low
	Nonroad mobile	low-medium	low-medium	low
	Stationary nonpoint	low	low	low
	Biogenic sources	low	low	low
	Other man-made sources (noncombustion)	medium	medium	low
HAP	Utilities	medium	medium	medium
	Other point sources	low-medium	low-medium	low
	On-road	low-medium	low-medium	low
	Nonroad mobile	low-medium	low-medium	low
	Stationary nonpoint	low	low	low
	Biogenic sources	low	low	low
	Other man-made sources (noncombustion)	low	low	low

Bergin and Milford (2000) applied a Bayesian Monte Carlo analysis to estimate uncertainties in ozone concentrations in a Lagrangian photochemical air quality model. Bayesian updating reduced the estimated uncertainty in predicted peak ozone concentrations. Beekmann and Derognat (2003) used a similar approach to analyze uncertainty in a Eulerian photochemical model (CHIMERE). Uncertainties in peak ozone ranged between ±15% and ±30%. Measurement constraint reduced uncertainties by a factor of 1.5 to 2.7.

Frey and Bammi (2002) estimated uncertainty in the emission factors for lawn and garden (L&G) equipment. For 2-stroke L&G engines, the 95% confidence intervals for the mean emission factors for total hydrocarbon (THC) and NO_x emissions were -30% to +41% and -45% to +75%, respectively. For 4-stroke L&G engines, the confidence intervals were -33% to +46% for THC and -27% to +35% for NO_x.

Frey and Li (2003) applied quantitative methods for characterizing variability and uncertainty to case studies of emission factors from AP-42 for stationary natural gas-fueled internal combustion engines. The approximate range of uncertainty in mean emission factors varies from as little as ±10% to as much as -60% to +80%, depending on the pollutant, control technology, and nature of the available data.

Frey and Zheng (2002a) developed a probabilistic methodology for quantifying variability and uncertainty in highway vehicle emission factors based on data used in MOBILE5b. Empirical distributions of emissions measurement data were used to characterize variability, while the bootstrap simulation method was used to characterize uncertainty. Inter-vehicle variability in emissions was found to span 2 or 3 orders of magnitude. The uncertainty in fleet average emission factors ranged from ±10% to as much as -90% to +280%.

Frey and Zheng, (2002b) quantified the variability and uncertainty in emission factors and activity factors for power plant NO_x emissions using the Monte Carlo and bootstrap simulation. The uncertainties were then propagated through an emission inventory to produce a probabilistic power plant NO_x emission inventory for North Carolina.

Frey and Bammi (2003) estimated variability and uncertainty in NO_x and total hydrocarbon emission factors for construction, farm, and industrial (non-road) engines. Bootstrap simulations were used to develop confidence intervals for the mean. The 95% confidence intervals for the mean emission factors were as small as –10 to +11% and as large as –48 to +49%, with an average range of –26 to +27%.

Abdel-Aziz and Frey (2003a) used univariate stochastic time series models, and ordinary least-squares regression models were employed to quantify hourly uncertainty in capacity emission factors and heat rate, respectively. The models were used to develop an hourly probabilistic power plant NO_x emission inventory for a four-day period. Abdel-Aziz and Frey (2003b) used multivariate time series models (time series approach) to account for the dependence between emissions from correlated units.

Zhao and Frey (2004) developed probabilistic toxic emission inventories for 1,3-butadiene, mercury, arsenic, benzene, formaldehyde, and lead for Jacksonville, Florida. Parametric and empirical bootstrap simulations were used to quantify the uncertainty in urban air toxic emission factors. The emission inventory 95% uncertainty ranges were as small as -25% to +42% for chromium to as large as -75% to +224% for arsenic with correlated surrogates. Uncertainty was dominated by only a few source categories. Using a similar approach, Frey and Zhao (2004) developed a probabilistic inventory of urban toxic emissions of benzene, formaldehyde, chromium, and arsenic for Houston, Texas. Maximum likelihood estimation was used to deal with censored (non-detected) values in emission data, and bootstrap simulation in combination with maximum likelihood estimation was used to estimate uncertainty in the mean emission factors. Zhao and Frey (2006) used maximum likelihood estimation and bootstrap simulation to determine asymptotically unbiased mean values and uncertainty for air toxic emission factors. Uncertainty in the mean was also estimated. The largest range of uncertainty in the mean was obtained for the external coal combustion benzene emission factor, with 95th confidence interval of the mean equal to -93% to +411%.

Chi et al. (2004) used bootstrap sampling, expert elicitation, and MC simulations to characterize uncertainty of nonroad emissions for Georgia from the EPA NONROAD model. Tools used were a bootstrap resampling technique and a parametric bootstrap analysis method in

Zheng and Frey's Analysis of Uncertainty and Variability Tool (AuvTool). Overall uncertainty ranged from -23 to +33%; however, fuel consumption, growth factors, equipment age distributions, PM and HC speciation profiles, temporal activity adjustments, fuel sulfur effects, and evaporative emissions were not accounted for in the analysis.

Meteorological and Air Quality Models

Derwent and Hov (1988) made estimates of uncertainty in photochemical model inputs based on "best judgments" for an application of sensitivity and analysis techniques. They estimated uncertainties to be ±50% for concentrations aloft; ±30% for emissions and deposition velocities, and hydroxyl radical sinks; ±20% for boundary layer depth; and ±10% wind speed. In preparation for an MC uncertainty analysis of Ozone Transport Assessment Group (OTAG) (1997) modeling, Frey (1998) developed estimates of uncertainty in the AQM inputs based on expert elicitation. Frey reported the uncertainty range, which includes 95% of the data, to be a factor of 5 for initial VOC and NO_x concentrations; a factor of 3 for initial ozone concentrations, boundary conditions of VOC and NO_x, and vertical diffusivity above 1000 m and at times other than 8:00 a.m. to 6:00 p.m.; and a factor of 2 for photolysis rates, cloud liquid water content, rainfall amounts, and emissions except major point sources. The range of uncertainty for chemical reactions in the Carbon Bond IV chemical mechanism varied, by reaction, from a factor of 1.01 to 3.02. The least uncertain model inputs were major point source emissions (±50%), horizontal boundary condition for ozone (±50%), concentrations aloft (±50%), wind direction (±40 degrees), cloud cover (±30%), vertical diffusivity below 1000 m from 8:00 a.m. to 6:00 p.m. (±30%), relative humidity (±30%), and ambient temperature (±3°C).

Yang et al. (1995) propagated uncertainties in reaction rate parameters, through simulations of urban ozone formation to estimated uncertainties in incremental reactivities of VOCs. Uncertainty ($\pm 1\sigma$) in reactivity ranged from 30% to 70%.

While formal estimates of uncertainty are not typically made of the meteorological model outputs used as inputs to AQMs, some information about uncertainty can be gained from the performance evaluations of these models. Often statistical comparisons of the model predictions to observations are provided. While these statistics provide a first-order estimate of the uncertainty, it must be kept in mind that model estimates and observations may not be spatially and temporally commensurate. Model predictions represent grid-cell volume averages of the predicted parameters at a particular time while observations are most often for a point location and may be averaged over various periods of time. Therefore, model performance-based estimates of uncertainty are likely to be larger than the actual uncertainty.

Olerud et al. (2000) performed meteorological modeling with MM5 for all of 1996 on a grid covering the entire continental United States at 36-km resolution. The results of this modeling have been used by EPA and regional planning organizations (RPOs) in subsequent air quality modeling studies with REMSAD, UAM-V, CAMx, and Community Multiscale Air Quality (CMAQ) model. The root mean square errors for the entire domain were reported by season and ranged from 1.15 to 1.47 m/s for wind speed, 35.2 to 38.5 degrees for wind direction, 2.3°C to 4.2°C for temperature, and 0.8 to 1.7 g/kg for humidity. Doty et al. (2002) reported on meteorological modeling with the RAMS model for the Southern Appalachian Mountains Initiative (SAMI). They found that for their 12-km domain, over all days modeled, the root mean square error for wind speed was 2.18 m/s, the gross error for wind direction was

39 degrees, the gross error for temperature was 1.9°C with a bias of –0.8°C, and the gross error for humidity was 0.8 g/kg with a bias of –0.1 g/kg.

Fish and Burton (1997) performed an uncertainty analysis on a Lagrangian photochemical model applied to stratospheric ozone destruction. Uncertainties in chemical kinetic and photochemical rate data were propagated through the modeling system. Arctic and mid-latitude ozone destruction could be modeled with ±25% and ±50% uncertainty (1 sigma), respectively. It was found that two reactions (out of more than 100) were responsible for more than a third of the uncertainty in the model calculations of Arctic ozone loss.

Moore and Londergan (2001) used a modification of the basic MC method to determine uncertainty. The computationally intensive aspects of the full methodology are replaced by a highly restricted sampling approach that exploits the spatial persistence found in predicted concentration fields. The approach was tested in an application of UAM-IV to assess the uncertainty in the differences in predicted maximum ozone concentration between the base-case and control scenarios. Uncertainty in model inputs and parameters were simulated using stochastic models driven by LHS. They propagated uncertainty in 168 model inputs for emissions, chemistry, meteorology, and boundary conditions.

A probabilistic hourly NO_x emission inventory was developed for 32 units of nine coal-fired power plants in the Charlotte, North Carolina, region for 1995 (Abdel-Aziz and Frey, 2003a,b). The uncertainty was then propagated through the MAQSIP model to estimate the uncertainty in maximum 1-hr and 8-hr concentrations for the Charlotte, North Carolina, modeling domain using an MC simulation (Abdel-Aziz and Frey, 2004). Statistical dependencies between power plant units (inter-unit variability), as well as temporal autocorrelation for each individual unit (intra-unit variability), were accounted for. A total of 50 simulations were performed to represent the ranges of uncertainty in hourly emissions and predicted ozone levels. The range of uncertainty in predicted peak 1-hr ozone concentrations solely attributable to utility NO_x emissions was as large as 25 ppb. Uncertainties in peak ozone concentrations at specific locations could be pinpointed to emissions from a specific power plant. Exceedances of the 8-hr standard were more widespread and not attributable to any one plant.

Mallet and Sportisse (2006) estimated uncertainty in a chemistry transport model due to physical parameterizations and numerical approximations using an ensemble modeling approach. The turbulent closure parameterization and chemical mechanism introduced the highest uncertainties.

Zhang et al. (2007) ran an ensemble of meteorological simulations with perturbed initial conditions through CMAQ to explore the sensitivity of ozone predictions caused by small meteorological perturbations. Significant uncertainties in ozone predictions for the Houston area were attributed to meteorological uncertainties, particularly from wind and temperature.

Expert Elicitation

Quantifying the uncertainties in model input variables may be difficult because there is little specific information on this subject in the literature for the complete spectrum of inputs (e.g., initial and boundary conditions, emissions components, meteorological variables, model parameterization constants, photolysis rates, and chemical rate constants). When quantifying the uncertainties is difficult, Morgan and Henrion (1990) suggest that it is appropriate to carry out an expert elicitation where "experts" are asked to give estimates of uncertainties based on their experience. To combine information from a number of different experts, each expert can be assigned a subjective weight indicating the relative extent of the individual's expertise with respect to the other experts participating in the elicitation (National Council on Radiation Protection and Measurements [NCRP], 1996). In many instances, each expert may be given equal weight, but in those areas for which the degree of expertise differs markedly, unequal weights may be assigned to each expert.

Hanna et al. (1998) estimated uncertainties in model inputs by taking the median of the uncertainty values (expressed as a plus and minus percentile that would include 95% of the variability) suggested by 10 modelers (experts) who responded to questionnaires. That is, each expert was given equal weight. In that study, no attempt was made to carry out a comprehensive survey of modelers (experts) or to encourage discussions among modelers.

Hanna et al. (2001) improved on this process by attempting to reach about 100 experts via a web page where the experts could enter their estimates of input uncertainties. The 100 experts included 10 or 20 from each major category of input data (e.g., emissions, boundary and initial conditions, chemical rate constants, and meteorology). However, only about 20 experts responded to the request. It was found that better information could be obtained by meeting with groups of experts at several different laboratories. One reason for the difficulty is that many photochemical modeling experts have not thought much about uncertainties in input parameters and, therefore, the estimates are largely based on intuition and compromise. Hanna et al. suggested that future expert elicitations should be more thorough, including workshops where experts come together to discuss the uncertainties. Experts should also assign weights to themselves based on their degree of expertise. The problem with the approach is that it is time-consuming and resource-intensive (two or three weeks of effort over a time period of about six months plus travel costs for two or three meetings for each of about 20 experts).

Uncertainties in BEIS3 biogenic emission outputs have been thoroughly examined. Hanna et al. (2002) used a Monte Carlo approach, while Hanna and Wilkinson (2004) used an analytical approach. The analytical equations for relative uncertainties agreed approximately with the results of the full Monte Carlo method. The total relative variance in isoprene emissions varied from 0.10 to 0.40, depending on temperature. The total oxygenated volatile organic compounds and monoterpene relative variances were similar, with values ranging from 0.10 to 0.26. They estimated that the relative uncertainty in BEIS3 emissions was in the range of about 0.3 to 0.8 (i.e., ± 30% to 80%). Hanna et al. (2003, 2005) evaluated consequences of the BEIS3 uncertainties in chemical transport models (CTMs). The MC uncertainties in the CTM-predicted 1-hr and 8-hr averaged ozone concentrations were studied by drawing 20 random samples from the 1000 sets of BEIS3 outputs and running each CTM (MAQSIP, UAM-V, and URM) 20 times for the three episodes. The estimated total uncertainties of ±15 to 20% are found to be nearly the same for the three CTMs over the three time periods, for 1-hr and 8-hr averages.

Winiwarter and Rypdal (2001) estimated uncertainty associated with the Austrian Greenhouse Gas emission inventory for CO_2, CH_4, and N_2O, and for the overall greenhouse potential. Expert elicitation was used to obtain uncertainties in inventory input data. Error distributions were then developed and combined using MC analysis. Overall uncertainty for all sources and gases was 10.5% and 12%, respectively. Uncertainties were attributed to N_2O emissions from soils, CH_4 from landfills, and CO_2 sinks in forests.

RELIABILITY OF INTEGRATED MODELING SYSTEMS

Much of the available literature on uncertainty in models only addresses the model's sensitivity to model inputs within their range of uncertainty. However, sensitivity to an input does not mean that the sensitivity will influence the IAQMS's response to emission changes. The literature in general indicates that when an IAQMS exhibits reasonable model performance, the system's response to emission changes may be more reliable than its ability to estimate absolute concentrations at monitoring sites.

Relative Response of Models

Hogrefe et al. (2008) suggest that operational model evaluation metrics provide little insight into the reliability of the actual model application in a regulatory setting (i.e., the estimation of relative changes), and that more emphasis should be placed on the development of dynamic evaluation approaches that test model response to changes in emission and meteorology. As a demonstration, Hogrefe et al. (2008) simulated an emission reduction scenario using two different vertical mixing parameterizations. While the model-to-model differences in daily maximum 8-hr ozone concentrations were up to 20 ppb, only minor differences were detected in the relative response of ozone concentrations to emission reductions, resulting in differences of a few ppb or less in estimated future year design values.

Jones et al. (2005) assessed the sensitivity and reliability of the RRF approach in the development of 8-hr ozone attainment plans. They examined the sensitivity of model-predicted responses to emission reductions to the choice of meteorology and chemistry mechanism. The different simulations agreed on whether predicted future-year design values would be above or below the NAAQS threshold at nearly 95% of the monitoring locations in the domain. Jones et al. (2005) also tested the ability of the attainment demonstration procedure to predict changes in monitored ozone design values through a retrospective analysis. An average gross error of around 5 ppb was found between modeled and observed design values. Also, at 27% of sites, model-predicted and observed design values disagreed as to whether the design value was above or below the NAAQS threshold.

Sistla et al. (2004) assert the need to provide uncertainty estimates of predicted RRFs. An operational assessment found that model-to-model differences could introduce an uncertainty in the future estimated design value of 3 to 5 ppb.

Dynamic Evaluation of Models

Dennis et al. (2008) reviews approaches to the evaluation of regional-scale air quality modeling systems, and introduces a conceptual model evaluation framework to provide a context for the evaluation process. The framework involves the complementary application of operational, diagnostic, dynamic, and probabilistic evaluation methods. Methods for each type of evaluation are reviewed, and examples of their application to air quality models are discussed. Data needs for model evaluation are also discussed.

Dennis et al. (2008) suggest that model performance methodologies developed for local and mesoscale model applications during the 1980s and 1990s may not extend for regional-scale applications. Model evaluation criteria should be dependent on the context of the application. Three primary objectives of air quality model evaluation are presented:

1. Determining the suitability of a modeling system for a specific application and configuration.
2. Distinguishing the performance among different models or different versions of the same model.
3. Guiding model improvement.

Dennis et al. (2008) define "dynamic evaluation" as an evaluation that assesses the ability of a model to predict changes in air quality concentrations in response to changes in source emissions or meteorology. A dynamic evaluation requires historical case studies where changes in emissions or meteorology are known, or can be confidently estimated, and the changes in emission or meteorology have a discernable impact on air quality. Cases that potentially meet these criteria include major regulatory programs (e.g., the NO_x SIP Call), cyclical emissions changes (e.g., day-of-the week mobile-source emission changes), and unique events (e.g., the 2003 black out).

Because air quality models are inherently deterministic, they do not explicitly account for uncertainties. A "probabilistic evaluation" attempts to qualify this uncertainty, but no specific widely used prescribed method exists. Ensemble methods are discussed by Dennis et al. (2008), and the authors note that results from a finite set of ensemble simulations are not a true measure of model uncertainty, as they represent only a limited view of a portion of the uncertainty spectrum. Monte Carlo techniques are also briefly discussed, and the authors note that input variables in air quality modeling systems can be correlated, which complicates the interpretation of results. Uncertainty in the model's relative response to emission reductions is briefly discussed, as are Bayesian approaches, rank order statistics, and extreme value theory. Dennis et al. (2008) conclude that regional air quality modeling systems cannot be validated in the formal sense, but can be shown to have predictive and diagnostic value.

Gilliland et al. (2008) suggest that "dynamic evaluation" is only possible if a retrospective case exists in which substantial emission reductions have resulted in discernable changes in air quality and the change in emissions can be quantified with reasonable confidence. They evaluated the CMAQ model's ability to predict ozone response to NO_x emission reductions associated with the NO_x SIP Call. Two different post-NO_x SIP Call summer periods were used to address the influence of meteorological changes on the ozone response. Simulations using SAPRC99, CB-IV, and CB-05 were performed to assess the sensitivity of ozone responses to the choice of chemical mechanism. CMAQ underestimated ozone reductions observed after the NO_x SIP Call was implemented. A spatial correlation analysis and comparison with aircraft ozone observations suggested that CMAQ underestimates the contribution of long-range transport of ozone and its precursors. Simulations using SAPRC more accurately predicted ozone response than simulations using CB-IV.

Recent research on modeling weekend/weekday ozone effects has used models as a tool to assess the causes of these effects for specific urban airsheds; however, they do not really address the issue of using the weekend/weekday as an observational basis for dynamic model evaluations. Yarwood et al. (2003) used CAMx to investigate hypotheses for the causes of weekday/weekend ozone differences in the Los Angeles area. They used first-order sensitivities calculated from DDM-3D in CAMx to study the contributions of VOC and NO_x reductions to weekday/weekend ozone changes. Jimenez et al. (2005) modeled weekend/weekday effects in the northeastern Iberian Peninsula.

Hogrefe et al. (2007) compared CMAQ weekend/weekday changes in ozone to observations. While they noted that weekend/weekday differences existed for observed and modeled ozone during summer 2001, the differences appeared to be mainly attributable to changes in meteorology. The authors suggested that to further compare observed and predicted weekend/weekday differences, methods to remove the effects of meteorological variations on ozone needed to be developed. They outlined steps for future research in this area, as they recognize the potential usefulness of using the weekend/weekday effect as a way to evaluate the modeling system's ability to reproduce observed response to emission changes.

A recent request for proposals from the Coordinating Research Council (CRC Project A-69, "Regional Modeling of Weekday/Weekend Ozone Changes") requires the contractor to perform a dynamic evaluation to test the ability of a regional modeling system to simulate ozone changes in response to weekday/weekend emission changes. They specifically reference Gilliland et al. (2008) as a source of useful approaches.

Marufu et al. (2004) used the August 2003 North American electrical blackout to quantify the direct contribution of power plants to regional haze and ozone. Aircraft observations collected over Pennsylvania, Maryland, and Virginia during the blackout were compared to observations taken during the previous summer in the same locations and under similar meteorological conditions. Marufu et al. (2004) found SO_2 and ozone reductions of 90% and 50% (7 ppb), respectively, and an improvement in visual range of > 40 km.

Hu et al. (2006) used CMAQ DDM-3D model simulations to quantify the effects of power plant emission reductions on SO_2 and ozone during the 2003 blackout. Sensitivity results show that the emission reductions led to SO_2 concentration reductions of 42%, sulfate concentration reductions of 22%, and ozone reductions of less than 5% (2 ppb), and that mobile NO_x emission reductions linked to the blackout had a larger impact on ozone than EGU NO_x emission reductions. The authors use these results to suggest that the observational results from Marufu et al. (2004) are overestimates.

Even though Hu et al. (2006) suggest that the Marufu et al. (2004) observational analysis overestimated ozone response to emission changes induced by the blackout, some recent SIPs (e.g., 2007 Baltimore Ozone SIP, New Jersey Ozone SIP) have used the results of Hu et al. (2006) as an authoritative argument that CMAQ underestimates ozone response to emission reductions.

UNCERTAINTIES IN THE IAQMS FOR THE SECOND PROSPECTIVE ANALYSIS

The Second Perspective Analysis is the first Section 812 analysis to use an integrated modeling system, the CMAQ model, to simulate national and regional-scale pollutant concentrations and deposition. The CMAQ model (National Exposure Research Laboratory, 1999) is a state-of-the-science, regional air quality modeling system that is designed to simulate the physical and chemical processes that govern the formation, transport, and deposition of gaseous and particulate species in the atmosphere. The CMAQ modeling system was designed to approach air quality as a whole by including state-of-the-science capabilities for modeling multiple air quality issues, including tropospheric ozone, fine particles, toxics, acid deposition, and visibility degradation. CMAQ was also designed to have multiscale capabilities so that separate models were not needed for urban- and regional-scale air quality modeling.

Douglas et al. (2008) applied the CMAQ model for seven core CAAA scenarios that include four different years that span a 30-year period: 1990, 2000, 2010, and 2020. Scenarios that incorporate the emission reductions associated with the CAA are referred to as *with-CAAA* while those that do not are referred to as *without-CAAA*. The scenarios include

- Retrospective Base-year Scenario
  - 1990 without-CAAA
- Base- and Future-year Scenarios without 1990 CAAA Controls
  - 2000 without-CAAA
  - 2010 without-CAAA
  - 2020 without-CAAA
- Base- and Future-year Scenarios with 1990 CAAA Controls
  - 2000 with-CAAA
  - 2010 with-CAAA
  - 2020 with-CAAA

For $PM_{2.5}$ and related species, the CMAQ model was applied in annual simulations for the period January through December. A 36-km resolution modeling domain that encompasses the contiguous 48 states was used for the annual modeling. For ozone and related species, the CMAQ model was applied for a five-month simulation period that captures the key ozone-season months of May through September. Two 12-km resolution modeling domains (that when combined cover the contiguous 48 U.S. states) were used for the ozone-season modeling.

E. H. Pechan & Associates, Inc. (E. H. Pechan & Associates, Inc. and Industrial Economics, Inc. 2006; Wilson et al., 2008) developed the base and projection year emission estimates that were used in the CMAQ modeling. These emission inventories have several unique features. One is the use of consistent economic assumptions from the Department of Energy's Annual Energy Outlook 2005 (AEO 2005) projections as the basis for estimating 2010 and 2020 emissions for all sectors. Another is the analysis of the different emissions paths for both with and without CAAA scenarios. Other features of this analysis include being the first EPA analysis that uses the 2002 National Emission Inventory files as the basis for making 48-state emission projections, incorporating control factor files from RPOs that had completed emission projections at the time the analysis was performed, and modeling the emission benefits of the expected adoption of measures to meet the 8-hr ozone NAAQS, the Clean Air Visibility Rule, and the $PM_{2.5}$ NAAQS.

Model-ready meteorological input files for 2002 were provided by EPA for use in the CMAQ modeling. The meteorological inputs to CMAQ were developed with the fifth-generation Penn State/NCAR mesoscale model (MM5) (Grell et al., 1994). Dolwick et al. (2007) describe the 36-km and eastern 12-km MM5 modeling and model performance for the eastern 12-km domain. The western 12-km modeling used MM5 meteorology that was developed by the Western Regional Air Partnership (WRAP) (Kemball-Cook et al., 2005). Brewer et al. (2007) described the MM5 model performance on the eastern 12-km domain and a limited analysis of model performance on the 36-km domain. These 2003 meteorological fields were used and described in the technical support document for the final Locomotive/Marine Rule (U.S. Environmental Protection Agency, 2008). The most complete description of the 2002 MM5 evaluation for all domains is in a yet-to-be-released internal EPA document for the entire 2002 CMAQ modeling platform (Dolwick, 2008).

Uncertainties in IAQMS will be assessed using EPA's Response Surface Metamodels (RSMs) for ozone (U.S. Environmental Protection Agency, 2006a) and particulate matter (U.S. Environmental Protection Agency, 2006b). The RSMs are based on an approach known as air quality metamodeling that aggregates numerous pre-specified individual air quality modeling simulations into a multi-dimensional air quality "response surface". Simply, this metamodeling technique is a "model of the model" and has been shown to reproduce the results from an individual modeling simulation with little bias or error over the range of conditions for which they were developed. The RSM incorporates statistical relationships between model inputs and outputs to provide a real-time estimate of air quality changes. The RSM provides a wide breadth of model outputs, which we can use to assess the impact of emission uncertainties. This approach allows for the rapid assessment of air quality impacts of different combinations of emission levels.

While the RSM-based uncertainty assessments have not been documented yet, Table 3 provides an initial description of emissions, meteorological, and air quality uncertainties in the IAQMS based on our review of relevant literature. The literature demonstrates a continuing process of uncertainty identification and reduction over the past several decades. Of the three main components in the IAQMS, the emissions component is still the most complex and uncertain with uncertainties in quantity, composition, spatial and temporal allocation, and future year projection. The literature also shows significant improvements in the meteorological and air quality modeling components of the IAQMS with more complete and accurate representations of atmospheric physics and chemistry, larger modeling domains, finer grid-resolution, and longer (i.e., annual or seasonal) simulation lengths. The current meteorological models still show regional and season biases in variables that can influence $PM_{2.5}$ formation but the longer term simulations tend to ameliorate the effects of these biases and more clearly define the extent and magnitude of the biases. The air quality model used in the Second Prospective Analysis includes a more complete treatment of aerosol chemistry than used previously but has been shown to underestimate the formation of secondary organic aerosols. The availability of $PM_{2.5}$ measurements (mass and speciation) since the first prospective Analysis has greatly improved our ability to assess model performance and uncertainties in estimates of $PM_{2.5}$. However, the lack of an available model performance evaluation for the CMAQ 2002 base case modeling limits our ability to understand and quantify the modeling uncertainties and their effects in this analysis.

Uncertainties in Table 3 are separated into broad categories for types of models such as emissions, meteorological, and air quality. In cases where a particular uncertainty is poorly defined or the literature is out of date, the opinions of experts were relied upon to refine the available information. Uncertainties are ranked based on their potential to affect the specific model with which they are associated and their overall effect on the IAQMS response to emission changes.

Table 3. Uncertainties associated with the Integrated Air Quality Modeling System in the Second Prospective Analysis.

Page 1 of 3

Category [a]	Key Uncertainties Associated with Emissions Estimation Potential Source of Error	Direction of Potential Bias for Net Benefits Estimate	Likely Significance Relative to Key Uncertainties in Net Benefit Estimate [b]
E	Uncertainties in biogenic emissions inputs increase uncertainty in the AQM estimates. Uncertainties in biogenic emissions may be large (± 80%). The biogenic inputs affect the emissions-based VOC/NOx ratio and, therefore, potentially affect the response of the modeling system to emissions changes.	Underestimate. The underestimate of biogenic emissions would reduce overall reactivity leading to underestimates of the model's response to emission reductions.	Potentially major. Impacts for ozone and $PM_{2.5}$ results. Both oxidation potential and secondary organic aerosol formation could influence $PM_{2.5}$ formation significantly. However, ozone benefits contribute only minimally to net benefit projections in this study.
E	The *with-CAAA* scenario includes implementation of the Clean Air Mercury Rule (CAMR), which has been vacated, and Clean Air Interstate Rule (CAIR), which was vacated but has since been remanded.	Overestimate.	Potentially major. Significance in 2020 will depend on the speed and effectiveness of implementing CAIR and replacing CAMR. In some areas, emissions reductions are expected to be overestimated, but in other areas, NO_x inhibition of ozone leads to underestimates of ozone benefits (e.g., some urban centers).
E	VOC emissions are dependent on evaporation, and future patterns of temperature are difficult to predict.	Overestimate.	Probably minor. An acceleration of climate change (warming) could increase emissions but the increase over 30 years would not likely be significant.
E	Use of average temperatures (i.e., daily minimum and maximum) in estimating motor-vehicle emissions artificially reduces variability in VOC emissions.	Unable to determine based on current information.	Probably minor. Use of averages will overestimate emissions on some days and underestimate on other days. Effect is mitigated in *with-CAAA* scenarios because of more stringent evaporative controls that are in place by 2000 and 2010.

Table 3. Uncertainties associated with the Integrated Air Quality Modeling System in the Second Prospective Analysis.

Category [a]	Key Uncertainties Associated with Emissions Estimation Potential Source of Error	Direction of Potential Bias for Net Benefits Estimate	Likely Significance Relative to Key Uncertainties in Net Benefit Estimate [b]
E	Economic growth factors used to project emissions are an indicator of future economic activity. These growth factors reflect uncertainty in economic forecasting as well as uncertainty in the link to emissions. IPM projections may be reasonable regionally but may introduce significant biases locally. Also, the Annual Energy Outlook 2005 growth factors do not reflect the recent economic downturn or the volatility in fuel prices since the fall of 2005.	Unable to determine based on current information.	Probably minor. The same set of growth factors are used to project emissions under both the *without-CAAA* and *with-CAAA* scenarios, mitigating to some extent the potential for significant errors in estimating differences in emissions. Some specific locations may be more significantly influenced.
E	Uncertainties in the stringency, scope, timing, and effectiveness of *with-CAAA* controls included in projection scenarios.	Unable to determine based on current information.	Probably minor. Future controls could be more or less stringent, wide, or effective than projected. Timing of emissions reductions may also be affected.
E	Emissions estimated at the county level (e.g., low-level source and motor vehicle NO_x and VOC emissions) are spatially and temporally allocated based on land use, population, and other surrogate indicators of emissions activity. Uncertainty and error are introduced to the extent that area source emissions are not perfectly spatially or temporally correlated with these indicators.	Unable to determine based on current information.	Probably minor. Potentially major for estimation of ozone, which depends largely on VOC and NO_x emissions; however, ozone benefits contribute only minimally to net benefit projections in this study.
E	The location of the emissions reductions achieved from unidentified measures is uncertain. We currently treat these reductions as if they're achieved from non-point sources, but this may not be correct in all cases.	Unable to determine based on current information.	Probably minor. Impacts from these uncertainties would be localized and would not significantly change the overall net benefit estimate.

Category [a]	Key Uncertainties Associated with Emissions Estimation Potential Source of Error	Direction of Potential Bias for Net Benefits Estimate	Likely Significance Relative to Key Uncertainties in Net Benefit Estimate [b]
E	The on-road source emissions projections reflect MOBILE6.2 data on the composition of the vehicle fleet. If recent volatility fuel prices persists or if fuel prices rise significantly (like they did in 2007 and 2008), the motor vehicle fleet may include more smaller, lower-emitting automobiles and fewer small trucks (e.g., SUVs).	Underestimate	Probably minor.
M	Unknown meteorological biases in the 12-km western and 36-km MM5 domains due to the lack of model performance evaluations.	Unable to determine based on current information.	Probably minor. Other evaluations using 2002 and similar meteorology and CMAQ have shown reasonable model performance. Although potentially major affects on nitrate results in western areas with wintertime $PM_{2.5}$ problems.

Table 3. Uncertainties associated with the Integrated Air Quality Modeling System in the Second Prospective Analysis.

Page 3 of 3

Category [a]	Key Uncertainties Associated with Emissions Estimation Potential Source of Error	Direction of Potential Bias for Net Benefits Estimate	Likely Significance Relative to Key Uncertainties in Net Benefit Estimate [b]
M	Known metrological biases in the 12-km eastern MM5 domain. MM5 has a cold bias during the winter and early spring, and has a general tendency to underestimate the monthly observed precipitation. MM5's under prediction was greatest in the fall and least in the spring months.	Unable to determine based on current information.	Probably minor. These biases would likely influence $PM_{2.5}$ formation processes, which was modeled on the 36-km domain.
A	Secondary organic aerosol (SOA) chemistry. CMAQ version 4.6 has known biases (underprediction) in SOA formation.	Underestimate.	Probably minor. A significant portion of SOA forms from biogenic emissions.
A	The CMAQ modeling relies on a modal approach to modeling $PM_{2.5}$ instead of a sectional approach. The modal approach is effective in modeling sulfate aerosol formation but less effective in modeling nitrate aerosol formation than the sectional approach.	Unable to determine based on current information.	Probably minor in the eastern U.S. where annual $PM_{2.5}$ is dominated by sulfate. Potentially major in some western U.S. areas where $PM_{2.5}$ is dominated by secondary nitrate formation.
A	No model performance evaluation of CMAQ for 2002.	Unable to determine based on current information.	Probably minor. Other evaluations using 2002 and similar meteorology and CMAQ have shown reasonable model performance.

Category [a]	Key Uncertainties Associated with Emissions Estimation Potential Source of Error	Direction of Potential Bias for Net Benefits Estimate	Likely Significance Relative to Key Uncertainties in Net Benefit Estimate [b]
A	Ozone modeling relies on a 12-km grid, suggesting NO_x inhibition of ambient ozone levels may be under-represented in some urban areas. Grid resolution may affect both model performance and response to emissions changes.	Unable to determine based on current information.	Probably minor. Though potentially major ozone results in those cities with known NO_x inhibition, ozone benefits contribute only minimally to net benefit projections in this study. Grid size affects chemistry, transport, and diffusion processes, which in turn determine the response to changes in emissions, and may also affect the relative benefits of low-elevation versus high-stack controls.
A	Emissions estimated at the county level (e.g., low-level source and motor vehicle NO_x and VOC emissions) are spatially and temporally allocated based on land use, population, and other surrogate indicators of emissions activity. Uncertainty and error are introduced to the extent that area source emissions are not perfectly spatially or temporally correlated with these indicators.	Unable to determine based on current information.	Probably minor. Potentially major for estimation of ozone, which depends largely on VOC and NO_x emissions; however, ozone benefits contribute only minimally to net benefit projections in this study.

[a] Categories are E (emissions), M (meteorological model), or A (air quality model)

[b] The classification of each potential source of error is based on those used in the first prospective Analysis. The classification of "potentially major" is used if a plausible alternative assumption or approach could influence the overall monetary benefit estimate by approximately 5% or more; if an alternative assumption or approach is likely to change the total benefit estimate by less than 5%, the classification of "probably minor" is used.

The summary tables of key uncertainties that were prepared for the first prospective Analysis (Tables 4 and 5) are provided for comparison to uncertainties in the Second Prospective Analysis. Table 4 includes uncertainties associated with emissions estimation while Table 5 includes uncertainties associated with air quality modeling. Significant improvements are apparent in both the modeling systems and model inputs since the first prospective Analysis was performed. While there have been many improvements in emission inventories the largest improvements have occurred in the air quality modeling system and the availability of $PM_{2.5}$ measurements. The use of longer term simulations with a single "one atmosphere" model in the Second Prospective Analysis significantly reduces many of the original sources of error such as the use of multiple models, different physical and chemical mechanisms, inadequate grid resolution and spatial coverage, and lack of adequate secondary aerosol chemistry. The increased availability of $PM_{2.5}$ measurements has increased our ability to assess model performance, quantify biases and errors, and gain confidence in the modeling system's estimates. These improvements have reduced the uncertainty in the IAQMS and the overall analytical chain and allowed us to provide better estimates of the effect and significance of key uncertainties on the net benefit estimate.

Table 4. Key uncertainties associated with emissions estimation identified in the First Prospective Analysis.

Page 1 of 2

Potential Source of Error	Direction of Potential Bias for Net Benefits Estimate	Likely Significance Relative to Key Uncertainties in Net Benefit Estimate*
$PM_{2.5}$ emissions are largely based on scaling of PM_{10} emissions.	Overall, unable to determine based on current information, but current emission factors are likely to underestimate $PM_{2.5}$ emissions from combustion sources, implying a potential underestimation of benefits.	Potentially major. Source-specific scaling factors reflect the most careful estimation currently possible, using current emissions monitoring data. However, health benefit estimates related to changes in $PM_{2.5}$ constitute a large portion of overall CAAA-related benefits.
Primary $PM_{2.5}$ emissions estimates are based on unit emissions that may not accurately reflect composition and mobility of the particles. For example, the ratio of crustal to primary carbonaceous particulate material likely is high.	Underestimate. The effect of overestimating crustal emissions and underestimating carbonaceous emissions when applied in later stages of the analysis, is to reduce the net impact of the CAAA on primary $PM_{2.5}$ emissions by underestimating $PM_{2.5}$ emissions reductions associated with mobile source tailpipe controls.	Potentially major. Mobile source primary carbonaceous particles are a significant contributor to public exposure to $PM_{2.5}$. Overall, however, compared to secondary $PM_{2.5}$ precursor emissions, changes in primary $PM_{2.5}$ emissions have only a small impact on $PM_{2.5}$-related benefits.
The *with-CAAA* scenario includes implementation of a region-wide NOx emissions reduction strategy to control regional transport of ozone that may not reflect the NO_x controls that are actually implemented in a regional ozone transport rule.	Unable to determine based on current information.	Probably minor. Overall, magnitude of estimated emissions reductions is comparable to that in an expected future regional transport rule. In some areas of the 37 state region, emissions reductions are expected to be overestimated, but in other areas, NO_x inhibition of ozone leads to underestimates of ozone benefits (e.g., some eastern urban centers).

Table 4. Key uncertainties associated with emissions estimation identified in the First Prospective Analysis.

Page 2 of 2

Potential Source of Error	Direction of Potential Bias for Net Benefits Estimate	Likely Significance Relative to Key Uncertainties in Net Benefit Estimate*
VOC emissions are dependent on evaporation, and future patterns of temperature are difficult to predict.	Unable to determine based on current information.	Probably minor. We assume future temperature patterns are well characterized by historic patterns, but an acceleration of climate change (warming) could increase emissions.
Use of average temperatures (i.e., daily minimum and maximum) in estimating motor-vehicle emissions artificially reduces variability in VOC emissions.	Unable to determine based on current information.	Probably minor. Use of averages will overestimate emissions on some days and underestimate on other days. Effect is mitigated in *with-CAAA* scenarios because of more stringent evaporative controls that are in place by 2000 and 2010.
Economic growth factors used to project emissions are an indicator of future economic activity. They reflect uncertainty in economic forecasting as well as uncertainty in the link to emissions.	Unable to determine based on current information.	Probably minor. The same set of growth factors are used to project emissions under both the *without-CAAA* and *with-CAAA* scenarios, mitigating to some extent the potential for significant errors in estimating differences in emissions.
Uncertainties in the stringency, scope, timing, and effectiveness of *with-CAAA* controls included in projection scenarios.	Unable to determine based on current information.	Probably minor. Future controls could be more or less stringent, wide reaching (e.g., NO_x reductions in OTAG region - see above), or effective (e.g., uncertainty in realizing all Reasonable Further Progress requirements) than projected. Timing of emissions reductions may also be affected (e.g., sulfur emissions reductions from utility sources have occurred more rapidly than projected for this analysis).

* The classification of each potential source of error reflects the best judgment of the section 812 Project Team. The Project Team assigns a classification of “potentially major” if a plausible alternative assumption or approach could influence the overall monetary benefit estimate by approximately 5% or more; if an alternative assumption or approach is likely to change the total benefit estimate by less than 5%, the Project Team assigns a classification of “probably minor”.

Table 5. Key uncertainties associated with air quality modeling from the First Prospective Analysis.

Potential Source of Error	Direction of Potential Bias for Net Benefits Estimate	Likely Significance Relative to Key Uncertainties in Net Benefit Estimate*
PM_{10} and $PM_{2.5}$ concentrations in the East (RADM domain) are based exclusively on changes in the concentrations of sulfate and nitrate particles, omitting the effect of anticipated reductions in organic or primary particulate fractions.	Underestimate.	Potentially major. Nitrates and sulfates constitute major components of PM, especially $PM_{2.5}$, in most of the RADM domain and changes in nitrates and sulfates may serve as a reasonable approximation of changes in total PM_{10} and total $PM_{2.5}$. Of the other components, primary crustal particulate emissions are not expected to change between scenarios; primary organic carbon particulate emissions are expected to change, but an important unknown fraction of the organic PM is from biogenic emissions, and biogenic emissions are not expected to change between scenarios. If the underestimation is major, it is likely the result of not capturing reductions in motor vehicle primary elemental carbon and organic carbon particulate emissions.
The number of $PM_{2.5}$ ambient concentration monitors throughout the U.S. is limited. As a result, cross estimation of $PM_{2.5}$ concentrations from PM_{10} (or TSP) data was necessary to complete the "monitor level" observational data set used in the calculation of air quality profiles.	Unable to determine based on current information.	Potentially major. $PM_{2.5}$ exposure is linked to mortality, and avoided mortality constitutes a large portion of overall CAAA benefits. Cross estimation of $PM_{2.5}$, however, is based on studies that account for seasonal and geographic variability in size and species composition of particulate matter. Also, results are aggregated to the annual level, improving the accuracy of cross estimation.
Use of separate air quality models for individual pollutants and for different geographic regions does not allow for a fully integrated analysis of pollutants and their interactions.	Unable to determine based on current information.	Potentially major. There are uncertainties introduced by different air quality models operating at different scales for different pollutants. Interaction is expected to be most significant for PM estimates. However, important oxidant interactions are represented in all PM models and the models are being used as designed. The greatest likelihood of error in this case is for the summer period in areas with NO_x inhibition of ambient ozone (e.g., Los Angeles).

Potential Source of Error	Direction of Potential Bias for Net Benefits Estimate	Likely Significance Relative to Key Uncertainties in Net Benefit Estimate*
Future-year adjustment factors for seasonal or annual monitoring data are based on model results for a limited number of simulation days.	Overall, unable to determine based on current information.	Probably minor. RADM/RPM and REMSAD PM modeling simulation periods represent all four seasons and characterize the full seasonal distribution. Potential overestimation of ozone, due to reliance on summertime episodes characterized by high ozone levels and applied to the May-September ozone season, is mitigated by longer simulation periods, which contain both high and low ozone days. Also, underestimation of UAM-V western and UAM-IV Los Angeles ozone concentrations (see below) may help offset the potential bias associated with this uncertainty.

Table 5. Key uncertainties associated with air quality modeling from the First Prospective Analysis.

Potential Source of Error	Direction of Potential Bias for Net Benefits Estimate	Likely Significance Relative to Key Uncertainties in Net Benefit Estimate*
Comparison of modeled and observed concentrations indicates that ozone concentrations in the western states were somewhat underpredicted by the UAM-V model, and ozone concentrations in the Los Angeles area were underestimated by the UAM-IV model.	Unable to determine based on current information.	Probably minor. Because model results are used in a relative sense (i.e., to develop adjustment factors for monitor data) the tendency for UAM-V or UAM to underestimate absolute ozone concentrations would be unlikely to affect overall results. To the extent that the model is not accurately estimating the relative changes in ozone concentrations across regulatory scenarios, the effect could be greater.
Ozone modeling in the eastern U.S. relies on a relatively coarse 12-km grid, suggesting NO_x inhibition of ambient ozone levels may be under-represented in some eastern urban areas. Coarse grid may affect both model performance and response to emissions changes.	Unable to determine based on current information.	Probably minor. Though potentially major for eastern ozone results in those cities with known NO_x inhibition, ozone benefits contribute only minimally to net benefit projections in this study. Grid size affects chemistry, transport, and diffusion processes, which in turn determine the response to changes in emissions, and may also affect the relative benefits of low-elevation versus high-stack controls. However, the approach is consistent with current state-of-the-art regional-scale ozone modeling.
UAM-V modeling of ozone in the western U.S. uses a coarser grid than the eastern UAM-V (OTAG) or UAM-IV models, limiting the resolution of ozone predictions in the west.	Unable to determine based on current information.	Probably minor. Also, probably minor for ozone results. Grid cell-specific adjustment factors for monitors are less precise for the west and may not capture local fluctuations. However, exposure tends to be lower in the predominantly non-urban west, and models with finer grids have been applied to three key population centers with significant ozone concentrations. May result in underestimation of benefits in the large urban areas not specifically modeled (e.g., Denver, Seattle) with finer grid.

Potential Source of Error	Direction of Potential Bias for Net Benefits Estimate	Likely Significance Relative to Key Uncertainties in Net Benefit Estimate*
Emissions estimated at the county level (e.g., area source and motor vehicle NO_x and VOC emissions) are spatially and temporally allocated based on land use, population, and other surrogate indicators of emissions activity. Uncertainty and error are introduced to the extent that area source emissions are not perfectly spatially or temporally correlated with these indicators.	Unable to determine based on current information.	Probably minor. Potentially major for estimation of ozone, which depends largely on VOC and NO_x emissions; however, ozone benefits contribute only minimally to net benefit projections in this study.

Table 5. Key uncertainties associated with air quality modeling from the First Prospective Analysis.

Potential Source of Error	Direction of Potential Bias for Net Benefits Estimate	Likely Significance Relative to Key Uncertainties in Net Benefit Estimate*
The REMSAD model underpredicted western PM concentrations during fall and winter simulation periods.	Unable to determine based on current information.	Probably minor. Because model results are used in a relative sense (i.e., to develop adjustment factors for monitor data) REMSAD's underestimation of absolute PM concentrations would be unlikely to significantly affect overall results. To the extent that the model is not accurately estimating the relative changes in PM concentrations across regulatory scenarios, or the individual PM components (e.g., sulfates, primary emissions) do not vary uniformly across seasons, the effect could be greater.
Lack of model coverage for acid deposition in western states.	Underestimate.	Probably minor. Because acid deposition tends to be a more significant problem in the eastern U.S. and acid deposition reduction contributes only minimally to net monetized benefits, the monetized benefits of reduced acid deposition in the western states would be unlikely to significantly alter the total estimate of monetized benefits.
Uncertainties in biogenic emissions inputs increase uncertainty in the AQM estimates.	Unable to determine based on current information.	Probably minor. Potentially major impacts for ozone outputs, but ozone benefits contribute only minimally to net benefit projections in this study. Uncertainties in biogenics may be as large as a factor of 2 to 3. These biogenic inputs affect the emissions-based VOC/NO_x ratio and, therefore, potentially affect the response of the modeling system to emissions changes.

* The classification of each potential source of error reflects the best judgment of the section 812 Project Team. The Project Team assigns a classification of "potentially major" if a plausible alternative assumption or approach could influence the overall monetary benefit estimate by approximately 5% or more; if an alternative assumption or approach is likely to change the total benefit estimate by less than 5%, the Project Team assigns a classification of "probably minor".

REFERENCES

Abdel-Aziz A. and Frey H.C. (2003a) Development of hourly probabilistic utility NOx emission inventories using time series techniques: Part I–univariate approach. *Atmos. Environ.* **37**, 5379-5389.

Abdel-Aziz A. and Frey H.C. (2003b) Development of hourly probabilistic utility NO_x emission inventories using time series techniques: Part II–multivariate approach. *Atmos. Environ.* **37**, 5391-5401.

Abdel-Aziz A. and Frey H.C. (2004) Propagation of uncertainty in hourly utility NO_x emissions through a photochemical grid air quality model: a case study for the Charlotte, NC Modeling Domain. *Environ. Sci. Technol.* **38** (7), 2153-2160.

Alcamo J. and Bartnicki J. (1987) A framework for error analysis of a long-range transport model with emphasis on parameter uncertainty. *Bull. Am. Meteorol. Soc.* **21** (10), 2121-2131.

Balakrishnan S., Roy A., Ierapetritou M.G., Flach G.P., and Georgopoulos P.G. (2003) Uncertainty reduction and characterization for complex environmental fate and transport models: An empirical Bayesian framework incorporating the stochastic response surface method. *Water Resources Research* **39**, 1350-1362.

Balakrishnan S., Roy A., Ierapetritou M.G., Flach G.P., and Georgopoulos P.G. (2005) A comparative assessment of efficient uncertainty analysis techniques for the environmental fate and transport models: Application to the FACT model. *Journal of Hydrology* **307**, 204-218.

Balentine H.W., Dickson R.J., and Oliver W.R. (1994) Development of uncertainty estimates for the Grand Canyon Visibility Transport Commission Emissions Inventory. Radian Corporation technical memorandum, Sacramento, CA, December.

Beck M.B., Ravetz J.R., Mulkey L.A., and Barnwell T.O. (1997) On the problem of model validation for predictive exposure assessments. *Stochastic Environmental Research and Risk Assessment* **11** (3), 229-254 (DOI 210.1007/BF02427917).

Beekmann M. and Derognat C. (2003) Monte Carlo uncertainty analysis of a regional-scale transport chemistry model constrained by measurements from the atmospheric pollution over the Paris area (ESQUIF) campaign. *J. Geophys. Res.* **108**, 8559.

Benkovitz C.M. and Oden N.L. (1989) Individual versus averaged estimates of parameters used in large scale emissions inventories. Atmos. Environ. 23, 903-909.

Benkovitz C.M. (1985) Framework for uncertainty analysis of the NAPAP emissions inventory. Prepared for the U.S. Environmental Protection Agency, Air and Energy Engineering Research Laboratory, EPA/600/7-85/036.

Bergin M.S., Noblet G.S., Petrini K., Dhieux J.R., Milford J.B., and Harley R.A. (1999) Formal uncertainty analysis of a Lagrangian photochemical air pollution model. *Environ. Sci. Technol.* **33** (7), 1116-1126.

Bergin M.S. and Milford J.B. (2000) Application of Bayesian Monte Carlo analysis to a Lagrangian photochemical air quality model. *Atmos. Environ.* **34**, 781-792.

Bischof C.A., Carle A., Corliss G., Griewank A., and Hovland P. (1992) ADIFOR: Generating derivative codes from Fortran programs. *Scientific Programming* **1** (1), 11-29.

Brewer J., Dolwick P., and Gilliam R. (2007) Regional and local scale evaluation of MM5 meteorological fields for various air quality modeling applications, Presented at the *87th Annual American Meteorological Society Annual Meeting, San Antonio, TX, January 15-18*.

Calbo J., Pan W., Webster M., Prinn R.G., and McRae G.J. (1998) Parameterization of urban subgrid scale processes in global atmospheric chemistry models. *J. Geophys. Res.* **103** (D3), 3437-3451.

Carmichael G.R., Sandu A., and Potra F. (1997) Sensitivity analysis for atmospheric chemistry models via automatic differentiation. *Atmos. Environ.* **31**, 475-489.

Chang M., Cardelino C., Chameides W., and Chang W. (1993) An iterative procedure to estimate emission inventory uncertainties. Presented at the *Regional Photochemical Measurement and Modeling Studies Meeting of the Air & Waste Management Association, San Diego, CA, November*.

Chang M., Cardelino C., Hartley D., and Chang W. (1995) Inverse techniques for developing historical and future year emission inventories. Presented at *The Emission Inventory: Programs and Progress Specialty Conference of the Air & Waste Management Association, Research Triangle Park, NC, October 11-13*.

Chi T.R., Unal A.D., and Tian R.A. (2004) Uncertainty of NONROAD emissions in Georgia. Presented at the *U.S. Environmental Protection Agency's 13th Annual Emission Inventory Conference, Clearwater, FL, June 7-10*.

Cho S.-Y., Carmichael G.R., and Rabitz H. (1987) Sensitivity analysis of the atmospheric reaction-diffusion equation. *Atmos. Environ* **21**, 2589-2598 (doi:2510.1016/0004-6981(2587)90190-90199).

Chow J.C., Watson J.G., Lowenthal D.H., Solomon P.A., Magliano K., Ziman S., and Richards L.W. (1992) PM_{10} source apportionment in California's San Joaquin Valley. *Atmos. Environ.* **26A**, 3335-3354.

Claiborn C., Mitra A., Adams G., Bamesberger L., Allwine G., Kantamaneni R., Lamb B., and Westberg H. (1995) Evaluation of PM_{10} emission rates from paved and unpaved roads using tracer techniques. *Atmos. Environ.* **29**, 1075-1089.

Coats C.J.J. and . H.M.R. (1996) Fast emissions modeling with the Sparse Matrix Operator Kernel Emissions modeling system. Paper presented at *The Emission Inventory: Key to Planning, Permits, Compliance, and Reporting, Air and Waste Management Association, New Orleans, LA, September 4- 6*.

Cohan D.S., Hakami A., Hu Y., and Russell A.G. (2005) Nonlinear response of ozone to emissions: Source apportionment and sensitivity analysis. *Environ. Sci. Technol.* **39** (17), 6739-6748.

Conover W.J. (1971) *Practical nonparametric statistics*, 2nd Ed., Wiley, New York.

Dabdub D., DeHaan L.L., and Seinfeld J.H. (1999) Analysis of ozone in the San Joaquin Valley of California. *Atmos. Environ.* **33**, 2501-2514.

DaMassa J. (1992) Technical guidance document for photochemical modeling. Technical Support Division, California Air Resources Board, Sacramento, CA.

Deguillaume L., Beekmann M., and Menut L. (2007) Bayesian Monte Carlo analysis applied to regional-scale inverse emission modeling for reactive trace gases. *J. Geophys. Res.* **112**, D02307.

Deguillaume L., Beekmann M., and Derognat C. (2008) Uncertainty evaluation of ozone production and its sensitivity to emission changes over the Ile-de-France region during summer periods. *J. Geophys. Res.* **113**, D02304.

Dennis R.L., Fox T., Fuentes M., Gilliland A.B., Hanna S., Hogrefe C., Irwin J., Rao S.T., Scheffe R., Schere K., Steyn D., and Venkatram A. (2008) On the evaluation of regional-scale photochemical air quality modeling systems. *Atmosperic Environment* (submitted).

Derwent R. and Hov Ø. (1988) Application of sensitivity and uncertainty analysis techniques to a photochemical ozone model. *J. Geophys. Res.* **93** (D5), 5185-5199.

Deuel H.P., Douglas S.G., and Burton C.S. (1998) Estimation of modeling system noise for two applications of the UAM-V modeling system: one-hour ozone, eight-hour ozone, and ozone exposure. Final report the Utility Air Regulatory Group, C/O Hunton and Williams, Washington, D.C., and Southern Company Services, Inc., Birmingham, AL, by Systems Applications International., Inc., San Rafael. CA, SYSAPP-98/27, August.

Digar A., Cohan D.S., Cox D., Boylan J., Kim B., and Khan M. (2008) Incorporating uncertainty into air quality modeling and planning—a case study for Georgia. Presented at the *7th Annual Community Modeling and Analysis System (CMAS) Conference Chapel Hill, NC, Chapel Hill, NC, October 6-8*.

Dolwick P. (2008) Personal communication with personnel at the U.S. Environmental Protection Agency, December 22.

Dolwick P., Gilliam, R. Reynolds L. and Huffman, A. (2007) Regional and local-scale evaluation of the 2002 MM5 meteorological fields for various air quality modeling applications. Extended abstract for the *6th Annual CMAS Conference, Chapel Hill, NC, October 1-3.*

Doty K., Tesche T.W., McNally D.E., Timin B., Mueller S.F. (2002) Meteorological modeling for the Southern Appalachian Mountains Initiative (SAMI). Final report prepared by University of Alabama in Huntsville, Huntsville, AL, July.

Douglas S.G., Haney J.L., Hudischewskyj A.B., Myers T.C., and We i.Y. (2008) Second prospective analysis of air quality in the U.S.: air quality modeling. Draft report prepared for the Office of Policy Analysis and Review, U.S. Environmental Protection Agency, Research Triangle Park, NC, by ICF International, San Rafael, CA, September.

Dunker A.M. (1981) Efficient calculation of sensitivity coefficients for complex atmospheric models. *Atmos. Environ.* **15** (7), 1155-1161.

Dunker A.M. (1984) The decoupled direct method for calculating sensitivity coefficients in chemical kinetics. *J. Chem. Phys.* **81**, 2385.

Dunker A.M., Yarwood G., Ortmann J.P., and Wilson G.M. (2002) The decoupled direct method for sensitivity analysis in a three-dimensional air quality model—implementation, accuracy, and efficiency. *Environ. Sci. Technol.* **36** (13), 2965-2976.

E. H. Pechan & Associates, Inc. and Industrial Economics, Inc. (2006) Emissions Projections for the Clean Air Act Second Section 812 Prospective Analysis. Draft report prepared for U.S. Environmental Protection Agency Office of Policy Analysis and Review (OPAR), Washington, D.C., June.

Efron B., and Tibshirani R. (1991) Statistical data analysis in the computer age. *Science* **253**, 390-395.

Emission Inventory Improvement Program (1996) Evaluating the uncertainty of emission estimates. Final report prepared for the Quality Assurance Committee, Emission Inventory Improvement Program, by Radian Corporation, Research Triangle Park, NC, July.

Environment Canada (1994) Uncertainties in Canada's 1990 greenhouse gas emission estimates, a quantitative assessment. Prepared by T.J. McCann & Associates. Unpublished report. Ottawa, Ontario, March.

Fish D.J. and Burton M.R. (1997) The effect of uncertainties in kinetic and photochemical data on model predictions of stratospheric ozone depletion. *J. Geophys. Res.* **102**, 25537-25542.

Freeman D.L., Egami R.T., Robinson N.F., and Watson J.G. (1986) A method for propagating measurement uncertainties through dispersion models. *J. Air Pollut. Control Assoc.* **36**, 246-253.

Frey C.H. and Zheng J. (2002a) Probabilistic analysis of driving cycle-based highway vehicle emission factors. *Environ. Sci. Technol.* **36** (23), 5184-5191.

Frey H.C. (1997) Quantitative analysis of uncertainty and variability in environmental policy making. *Uncertainty Modeling and Analysis in Civil Engineering*, B.M. Ayyub ed., CRC Press, Washington, D.C.

Frey H.C. (1998) Estimates of uncertainty in air quality model inputs based upon expert elicitation. Prepared for Hanna Consultants, Kennebunkport, ME by North Carolina State University, Raleigh, NC, September.

Frey H.C., Bharvirkar R., and Zheng J. (1999) Quantitative analysis of variability and uncertainty in emissions estimation. Prepared for the U.S. Environmental Protection Agency, Research Triangle Park, NC, by North Carolina State University, Raleigh,NC, July.

Frey H.C. and Bammi S. (2002) Quantification of variability and uncertainty in lawn and garden equipment NO_x and total hydrocarbon emission factors. *J. Air & Waste Manag. Assoc.* **52** (4), 435-448.

Frey H.C. and Zheng J. (2002b) Quantification of variability and uncertainty in air pollutant emission inventories: method and case study for utility NO_x emissions. *J. Air & Waste Manag. Assoc.* **52** (9), 1083-1095.

Frey H.C. and Bammi S. (2003) Probabilistic nonroad mobile source emission factors. *J. Environ. Eng.* **129**, 162-168.

Frey H.C. and Zhao Y. (2004) Quantification of variability and uncertainty for air toxic emission inventories with censored emission factor data. *Environ. Sci. Technol.* **38**, 6094-6100.

Fujita E.M., Croes B.E., Bennett C.L., Lawson D.R., Lurmann F.W., and Main H.H. (1992) Comparison of emission inventory and ambient concentration ratios of CO, NMOG, and NO_x in California's South Coast Air Basin. *J. Air & Waste Manag. Assoc.* **42**, 264-276.

Gao D., Stockwell W.R., and Milford J.B. (1996) Global uncertainty analysis of a regional-scale gas-phase chemical mechanism. *J. Geophys. Res.* **101**, 9107-9119.

Gatz D.F., and Smith L. (1995a) The standard error of a weighted mean concentration - I. bootstrapping vs. other methods. *Atmos. Environ.* **29**, 1185-1193.

Gatz D.F., and Smith L. (1995b). Statistical data analysis in the computer age - I. estimating confidence intervals. *Atmos. Environ.* **29**, 1195-1200.

Gilliland A.B., Hogrefe C., Pinder R.W., Godowitch J.M., Foley K.L., and Rao S.T. (2008) Dynamic evaluation of regional air quality models: assessing changes in O_3 stemming from changes in emissions and meteorology. *Atmos. Environ.* **42**, 5110-5123.

Grell G.A., Dudhia J., and Stauffer D.R. (1994) A description of the fifth-generation Penn State/NCAR mesoscale model (MM5). Prepared by the National Center for Atmospheric Research, Boulder, CO, NCAR Technical Note-398.

Hakami A., Odman M.T., and Russell A.G. (2003) High-order, direct sensitivity analysis of multidimensional air quality models. *Environ. Sci. Technol.* **37** (11), 2442-2452.

Hakami A., Odman M.T., and Russell A.G. (2004) Nonlinearity in atmospheric response: a direct sensitivity analysis approach. *J. Geophys. Res.* **109**, D15303.

Hanna S.R., Chang J.C., and Fernau M.E. (1998) Monte Carlo estimates of uncertainties in predictions by a photochemical grid model (UAM-IV) due to uncertainties in input variables. *Atmos. Environ.* **32**, 3619-3628.

Hanna S.R., Lu Z., Frey H.C., Wheeler N., Vukovich J., Arunachalam S., Fernau M., and Hansen D.A. (2001) Uncertainties in predicted ozone concentrations due to input uncertainties for the UAM-V photochemical grid model applied to the July 1995 OTAG Domain. *Atmos. Environ.* **35** (5), 891-903 (ISSN 1352-2310).

Hanna S.R. and Davis J.M. (2002) Evaluation of a photochemical grid model using estimates of concentration probability density functions. *Atmos. Environ.* **36** (11), 1793-1798.

Hanna S.R., Russell A.G., Wilkinson J., and Vukovich J. (2003) Review of BEIS3 formulation and consequences relative to air quality standards: estimation of effects in uncertainties in BEIS3 emissions on uncertainties in ozone predictions by chemical transport models. Technical report prepared for EPRI, Palo Alto, CA, EPRI 1005244.

Hanna S.R. and Wilkinson J. (2004) Analytical estimation of uncertainties in biogenic emissions calculated by BEIS3 due to uncertainties in model inputs and parameters. Presented at the *U.S. Environmental Protection Agency's 13th Annual Emission Inventory Conference Clearwater, FL, June 7-10*.

Hanna S.R., Russell A.G., Wilkinson J.G., Vukovich J., and Hansen D.A. (2005) Monte Carlo estimation of uncertainties in BEIS3 emission outputs and their effects on uncertainties in chemical transport model predictions. *J. Geophys. Res.* **110**, D01302.

Hanna S.R., Paine R.J., Heinold D.W., Kintigh E., and Baker D. (2006) A Monte Carlo study of uncertainties in benzene and 1,3-butadiene concentrations calculated by AERMOD and ISC in the Houston ship channel area. Presented at the *14th Joint Conference on the Applications of Air Pollution Meteorology with the Air and Waste Management Association, Atlanta, GA, January 30-February 2*.

Hanna S.R., et al. (1998) Evaluations of Numerical Weather Prediction (NWP) models from the point of view of inputs required by atmospheric dispersion models. *5th International Conference on Harmonization within Atmospheric Dispersion Modeling for Regulatory Purposes, Rhodes, Greece, May 18-21*.

Harley R.A., Sawyer R.F., and Milford J.B. (1997) Updated photochemical modeling for California's south coast air basin: comparison of chemical mechanisms and motor vehicle emissions inventories. *Environ. Sci. Technol.* **31**, 2829-2839.

Hartley D., and Prinn R.J. (1993) Feasibility of determining surface emissions of trace gases using an inverse method in a three-dimensional chemical transport model. *J. Geophys. Res.* **98**, 5183-5197.

Hass H., Builtjes P.J.H., Simpson D., and Stern R. (1997) Comparison of model results obtained with several European regional air quality models. *Atmos. Environ.* **31**, 259-3279.

Hogrefe C., Rao S.T., Zurbenko I.G., and Porter P.S. (2000) Interpreting the information in ozone observations and model predictions relevant to regulatory policies in the eastern United States. *Bull. Am. Meteorol. Soc.* **81**, 2083-2106 (9). Available on the Internet at <http://dx.doi.org/10.1175/1520-0477(2000)081<2083:ITIIOO>2.3.CO;2>.

Hogrefe C., Jones J.M., Gilliland A., Porter P.S., Gégo E., Gilliam R., Swall J., Irwin J., and Rao S.T. (2007) Evaluation of an annual simulation of ozone and fine particulate matter over the continental United States—which temporal features are captured? *Air Pollution Modeling and Its Application XVII*, C. Borrego and A. Norman eds., Springer, United States (DOI 10.1007/978-0-387-68854-1).

Hogrefe C., Civerolo K.L., Hao W., Ku J.-Y., Zalewsky E.E., and Sistla G. (2008) Rethinking the assessment of photochemical modeling systems in air quality planning applications. *J. Air & Waste Manag. Assoc.* **58** (8), 1086-1099.

Horie Y. (1988) Handbook on Procedures for Establishing the Uncertainties of Emission Estimates. Prepared for the California Air Resources Board Research Division, by Valley Research Corporation, ARB Contract A5-184-32.

Horie Y. and Shorpe A.L. (1989) Development of procedures for establishing the uncertainties of emission estimates. Paper 89-24.7 presented at the *82nd Annual Air and Waste Management Association Meeting Anaheim, CA, June*.

Hossain F., Anagnostou E.N., and Lee K.-H. (2004) A non-linear and stochastic response surface method for Bayesian estimation of uncertainty in soil moisture simulation from a land surface model. *Nonlinear Process in Geophysics* **11**, 427-440.

Houyoux M.R., Loughlin D.H., Holland A.P., Frey H.C., and Abdel-Aziz A. (2003) Design, Application, and Recommendations for Including Inventory Uncertainties in Emission Inventory Preparation for Modeling. *12th International Emission Inventory Conference, Emission Inventories - Applying New Technologies, San Diego, April 29 - May 1*.

Hu Y., Odman M.T., and Russell A.G. (2006) Re-examination of the 2003 North American electrical blackout impacts on regional air quality. *Geophys. Res. Lett.* **33**, L22810.

Hubbell B. (2003) Identification of cost effectiveness measures using response-surface modeling. Presented at the *Symposium on Cost-Effectiveness Analysis for Multiple Benefits, Washington, D.C., September 9*.

Hwang D., Byun D., and Odman M.T. (1997) An automatic differentiation technique for sensitivity analysis of numerical advection schemes in air quality. *Atmos. Environ.* **31** (6), 879-888.

Iman R.L., and Helton J.C. (1988) An investigation of uncertainty and sensitivity analysis techniques for computer models. *Risk Analysis* **8**, 71-90.

International Atomic Energy Agency (1989) Evaluating the reliability of predictions made using environmental transfer models. prepared by the International Atomic Energy Agency, Vienna, Austria, IAEA Safety Series No. 100.

Irwin J.S., Rao S.T., Petersen W.B., and Turner D.B. (1987) Relating error bounds for maximum concentration estimates to diffusion meteorology uncertainty. *Atmos. Environ.* **21**, 1927-1937.

Isukapalli S.S., Roy A., and Georgopoulos P.G. (1998) Stochastic response surface methods (SRSMs) for uncertainty propagation: Application to environmental and biological systems. *Risk Anal.* **18** (3), 351-363.

Isukapalli S.S., Roy A., and Georgopoulos P.G. (2000) Efficient sensitivity/uncertainty analysis using the combined stochastic response surface method and automated differentiation: Application to environmental and biological systems. *Risk Anal.* **20** (5), 591-602.

Jang J.C.C., Jeffries H.E., and Tonnesen S. (1995) Sensitivity of Ozone to Model Grid Resolution-I. Detailed Process Analysis for Ozone Chemistry. *Atmos. Environ.* **29** (21), 3085-3100.

Jeffries H.E., Keating T., and Wang Z. (1996) Integrated process rate analysis of the impact of NO_x emission height on UAM-modeled peak ozone levels. Final topical report prepared for the Gas Research Institute, Chicago, IL.

Jeffries H.E. (1997) Use of integrated process rate analyses to perform source attribution for primary and secondary pollutants in Eulerian air quality models. Presented at the *U.S. EPA Source Attribution Workshop, Research Triangle Park, NC, July 16-18*.

Jimenez P., Parra R., Gasso S., and Baldasano J.M. (2004) Modeling the ozone weekend effect in very complex terrains: a case study in the Northeastern Iberian Peninsula. *Atmos. Environ.* **39** (3), 429-444.

Jin L., Tonse S., Cohan D.S., Mao X., Harley R.A., and Brown N.J. (2008) Sensitivity analysis of ozone formation and transport for a central California air pollution episode. *Environ. Sci. Technol.* **42** (10), 3683-3689.

Jones J.M., Hogrefe C., Henry R.F., Ku J.-Y., and Sistla G. (2005) An assessment of the sensitivity and reliability of the relative reduction factor (RRF) approach in the development of 8-hr ozone attainment plans. *J. Air & Waste Manag. Assoc.* **55** (1), 13-19.

Kemball-Cook, S., Jia Y., Emery C., Morris R., Wang Z., and Tonnesen G. (2005) Annual 2002 MM5 meteorological modeling to support regional haze modeling of the western United States. Report prepared for The Western Regional Air Partnership (WRAP), Denver, CO 80202, March.

Kini M.D. and Frey H.C. (1997) Probabilistic evaluation of mobile source air pollution. Prepared for the Center for Transportation and Environment by North Carolina State University, Raleigh, NC.

Linstone H.A. and Turoff M. (2002) *The Delphi Method, Techniques and Applications*, Addison-Wesley.

Lo C.S. and Jeffries H.E. (1997) A quantitative technique for assessing pollutant source location and process composition in photochemical grid models. Presented at the *Annual Air & Waste Management Association Meeting, Toronto, Ontario*.

Lowenthal D.H., Chow J.C., Watson J.G., Neuroth G.R., Robbins R.B., Shafritz B.P., and Countess R.J. (1992) The effects of collinearity in the ability to determine aerosol contributions from diesel- and gasoline-powered vehicles using the chemical mass balance model. *Atmos. Environ*. **26A**, 2341-2351.

Mallet V. and Sportisse B. (2006) Uncertainty in a chemistry-transport model due to physical parameterizations and numerical approximations: An ensemble approach applied to ozone modeling. *J. Geophys. Res.* **111**, D01302.

Mangat T.S., Robinson L.H., and Switzer P. (1984) Medians and percentiles for emission inventory totals. Presented at the *77th Annual Meeting of the Air Pollution Control Association, San Francisco, CA. June*.

Martien P.T., Harley R.A., and Cacuci D.G. (2006) Adjoint sensitivity analysis for a three-dimensional photochemical model: Implementation and method comparison. *Environ. Sci. Technol.* **40** (8), 2663-2670.

Marufu L.T., Taubman B.F., Bloomer B., Piety C.A., Doddridge B.G., Stehr J.W., and Dikerson R.W. (2004) The 2003 North American electrical blackout: An accidental experiment in atmospheric chemistry. *Geophys. Res. Lett.* **31**, L13106.

Menut L. (2003) Adjoint modeling for atmospheric pollution process sensitivity at regional scale. *J. Geophys. Res.* **108** (D17), 8562.

Milford J.B., Gao D., Russell A.G., and McRae G.J. (1992) Use of sensitivity analysis to compare chemical mechanisms for air-quality modeling. *Environ. Sci. Technol.* **26**, 1179-1189.

Mitchell W.J., Suggs J.C., and Streib E.W. (1995) A statistical analysis of stationary source compliance test audit data. *J. Air & Waste Manag. Assoc*. **45**, 83-88.

Moore G.E. and Londergan R.J. (2001) Sampled Monte Carlo uncertainty analysis for photochemical grid models. *Atmos. Environ.* **35**, 4863-4876.

Morgan M.G. and Henrion M. (1990) *Uncertainty: a guide to fealing with uncertainty in quantitative risk and policy analysis*, Cambridge University Press, New York, NY.

Mulholland M., and Seinfeld J.H. (1995) Inverse air pollution modelling of urban-scale carbon monoxide emissions. *Atmos. Environ*. **29**, 497-516.

Napelenok S.L., Cohan D.S., Hu Y., and Russell A.G. (2006) Decoupled direct 3D sensitivity analysis for particulate matter (DDM-3D/PM). *Atmos. Environ.* **40** (32), 6112-6121.

NARSTO (2005) *Improving emission inventories for effective air quality management across north america--a NARSTO assessment*, J.D. Mobley, ed., (NARSTO-05-001).

National Council on Radiation Protection and Measurements (1996) A guide for uncertainty analysis in dose and risk assessments related to environmental contamination. NCRP Commentary Number 14 prepared by the National Council on Radiation Protection and Measurements, Bethesda, MD, ed., F.O. Hoffman.

National Exposure Research Laboratory (1999) Science algorithms of the EPA Models-3 Community Multiscale Air Quality (CMAQ) modeling system. Report prepared by the National Exposure Research Laboratory, Research Triangle Park, NC, EPA/600/R-99/030 (peer reviewed), March.

Oden N.L. and Benkovitz C.M. (1990) Statistical implications of the dependence between the parameters used for calculations of large scale emissions inventories. *Atmos. Environ.* **24A** (3), 449-456.

Odman T. and Ingram C.L. (1996) Multiscale Air Quality Simulation Platform (MAQSIP): source code documentation and validation. MCNC Technical Report, ENV-96TR002-v1.0.

Olerud D., Alapaty K., and Wheeler N. (2000) Meteorological modeling of 1996 for the United States with MM5. Final report to the U.S. Environmental Protection Agency under task order number CAA689805, MCNC, Research Triangle Park, NC, September.

Ozone Transport Assessment Group (1997) OTAG regional and urban scale modeling, Version 1.1. Modeling Report.

Pan W., Tatang M.A., McRae G.J., and Prinn R.G. (1998) Uncertainty analysis of indirect radiative forcing by anthropogenic suflate aerosols. *J. Geophys. Res.* **103** (D4), 3815-3824.

Peer R.L., Epperson D.L., Campbell D.L., and von Brook P. (1992) Development of an empirical model of methane emissions from landfills. United States Environmental Protection Agency, Air and Energy Engineering Laboratory, Research Triangle Park, NC, EPA-600/R-92-037.

Pierson W.R., Gertler A.W., and Bradow R.L. (1990) Comparison of the SCAQS Tunnel Study with other on-road vehicle emission data. *J. Air & Waste Manag. Assoc.* **40** (11), 1495-1504.

Pollack A.K., Bhave P., Heiken J., Lee K., Shepard S., Tran C., Yarwood G., Sawyer R.F., and Joy B.A. (1999) Investigation of emission factors in the California EMFAC7G model. Prepared for the Coordinating Research Council by ENVIRON International Corporation, Novato, CA, PB99-149718NZ.

Rabitz H., Kramer M., and Docol D. (1983) Sensitivity analysis in chemical kinetics. *Annu. Rev. Phys. Chem.* **34**, 419-461.

Reynolds S.D., Michaels H.M., Roth P.M., Tesche T.W., McNally D., Gardner L., and Yarwood G. (1996) Alternative base cases in photochemical modeling: their construction, role and value. *Atmos. Environ.* **30** (12), 1977-1988.

Rhodes D.S. and Frey H.C. (1997) Quantification of variability and uncertainty in AP-42 emission factors using bootstrap simulation. *Air and Waste Management Association's Conference on Emission Inventory: Planning for the Future, Pittsburgh, PA, October*.

Rodriguez M.A. and Dabdub D. (2003) Monte Carlo uncertainty and sensitivity analysis of the CACM chemical mechanism. *J. Geophys. Res.* **108**, 1443.

Saeger M. (1994) Procedures for verification of emissions inventories, Final report. prepared for the Emissions Inventory Branch, Office of Air Quality Planning and Standards, U.S. Environmental Protection Agency, Research Triangle Park, NC, EPA Contract No. 68-D3-0030.

Scheff P.A., Wadden R.A., Kenski D.M., and Chang J. (1995) Receptor model evaluation of the SEMOS ambient NMOC measurements. Paper 95-113C.03. Presented at the *88th Annual Meeting of the Air Pollution Control Association, San Antonio, Texas, June*.

Schere K.L. and Coats C.J. (1992) A stochastic methodology for regional wind-field modeling. *J. Appl. Meteor.* **31**, 1407-1425.

Seefeld S. and Stockwell W.R. (1999) First-order sensitivity analysis of models with time-dependent parameters: an application to PAN and ozone. *Atmos. Environ.* **33**, 2941-2953.

Seigneur C., Tesche T.W., Roth P.M., and Reid L.E. (1981) Sensitivity of a complex urban air quality model to input data. *J. Appl. Meteorol.* **20**, 1020-1040.

Sistla G., Hogrefe C., Hao W., Ku J.-Y., Zalewsky E., Henry R.F., and Civerolo K. (2004) An operational assessment of the application of the relative reduction factors in the demonstration of attainment of the 8-hr ozone national ambient air quality standard. *J. Air & Waste Manag. Assoc.* **54** (8), 950-959.

Solarski R.S., Butler D.M., and Rundel R.D. (1978) Uncertainty propogation in a stratospheric model, 2. Monte Carlo analysis of imprecisions due to reaction rates. *J. Geophys. Res.* **83**, 3074-3078.

South Coast Air Quality Management District (SCAQMD) (1982) Uncertainty of 1979 emissions data, Chapter IV: 1983 Air Quality Management Plan Revision, Appendix IV-A; 1979 Emissions Inventory for the South Coast Air Basin, Revised October 1982. Planning Division, El Monte, California. October.

Spellicy F.L., Draves J.A., Crow W.L., Herget W.F., and Buchholtz W.F. (1992) A demonstration of optical remote sensing in a petrochemical environment. Presented at the A*ir & Waste Management Association Specialty Conference on Remote Sensing, Houston, TX, April 6-9*.

Steiner C.K.R., Gardner L., Causley M.C., Yocke M.A., and Steorts W.L. (1994) Inventory quality issues associated with the development of an emissions inventory for the Minerals Management Service Gulf of Mexico Air Quality Study. In *The Emission Inventory: Perception and Reality: Proceedings of an International Specialty Conference, VIP-38. Air & Waste Management Association*, Pittsburgh, Pennsylvania.

Straume A.G., N'Dri Koffi E., and Nodop K. (1998) Dispersion modeling using ensemble forecasts compared to ETEX measurements. *J. Applied Meteorology* **37**, 1444-1456.

Tatang M.A., Pan W., Prinn R.G., and McRae G.J. (1997) An efficient method for parametric uncertainty analysis of numerical geophysical models. *J. Geophys. Res.* **102**, 21925-21932.

U.S. Environmental Protection Agency (1995) Compilation of air pollutant emission factors, volume I: stationary point and area sources, Fifth Edition, AP-42. U.S. Environmental Protection Agency, Office of Air Quality Planning and Standards. Research Triangle Park, NC.

U.S. Environmental Protection Agency (1999) Draft guidance on the use of models and other analyses in attainment demonstrations for the 8-hour ozone NAAQS. Prepared by the Office of Air Quality Planning and Standards, U.S. Environmental Protection Agency, Research Triangle Park, NC, EPA-454/4-99-004.

U.S. Environmental Protection Agency (2001) Draft guidance for demonstrating attainment of air quality goals for $PM_{2.5}$ and regional haze, Draft 2.1. Prepared by the Office of Air Quality Planning and Standards, U.S. Environmental Protection Agency, Research Triangle Park, NC, January.

U.S. Environmental Protection Agency (2006a) Technical support document for the proposed Mobile Source Air Toxics Rule: Ozone modeling. Prepared by the U.S. Environmental Protection Agency, Office of Air Quality Planning and Standards, Research Triangle Park, NC, February.

U.S. Environmental Protection Agency (2006b) Technical support document for the proposed PM NAAQS rule: response surface modeling. U.S. Environmental Protection Agency, Office of Air Quality and Planning Standards, Research Triangle Park, NC. Available on the Internet at <http://www.epa.gov/scram001/reportsindex.htm>, February

U.S. Environmental Protection Agency (2007) Technical support document for the final Mobile Source Air Toxics Rule: Ozone modeling. Prepared by Air Quality Assessment Division, Office of Air Quality Planning and Standards, U.S. Environmental Protection Agency, Research Triangle Park, NC, EPA454/R-07-003, February. Available on the Internet at <http://epa.gov/otaq/regs/toxics/454r07003.pdf>.

U.S. Environmental Protection Agency (2008) Technical support document for the final locomotive/marine rule: air quality modeling analyses, EPA-454/R-08-002, January.

Vuilleumier L., Brown N.J., Orlando E., Harley R.A., and Reynolds S.D. (2000) Review and improvement of methods for estimating rates of photolysis in photochemical models. Final report prepared for California Air Resources Board and the California Environmental Protection Agency, Sacramento, CA, by Lawrence Berkeley National Laboratory, Berkeley, CA, Contract No. 96-335, December.

Wagner K.K. and Wheeler N.J.M. (1988) 1995 Ozone modeling boundary condition sensitivity. Memorandum prepared by the Modeling and Meteorology Branch, California Air Resources Board, July.

Wagner K.K. and Wheeler N.J. (1989) Variability of photochemical modeling emission sensitivity with respect to meteorology. Preprints from the *Sixth Joint Conference on Applications of Air Pollution Meteorology, Anaheim, CA, January 30–February 3*, 222-223, American Meteorological Society.

Wagner K.K., Wheeler N.J.M., and McNerny D.L. (1992) The effect of emission inventory uncertainty on Urban Airshed Model sensitivity to emission reductions. In Transactions of an international conference *Tropospheric Ozone: Nonattainment and Design Value Issues*, TR-23, 123-134, J.J. Vostal, ed., Air and Waste Management Association.

Wang L., Milford J.B., and Carter W.P.L. (2000) Reactivity estimates for aromatic compounds. Part 2: Uncertainty in incremental reactivities. *Atmos. Environ.* **34**, 4349-4360.

Watson J.G., Cooper J.A., and Huntzicker J.J. (1984) The effective variance weighing for least squares calculations applied to the mass balance receptor model. *Atmos. Environ.* **18,** 1347-1355.

Webster M. and Sokolov A.P. (2000) A methodology for quantifying uncertainty in climate projections. *Climatic Change* **46**, 417-446.

Webster M., Scott J., Sokolov A.P., and Stone P. (2006) Estimating probability distributions from complex models with bifurcations: the case of ocean circulation collapse. Prepared by the MIT Joint Program on the Science and Policy of Global Change, Report No. 133, March.

Wheeler N.J.M. (1992) Urban Airshed Model sensitivity to horizontal transport paths. In Transactions of an international conference *Tropospheric Ozone and the Environment II: Effects, Modeling and Control, Atlanta, GA, November 5-7, 1991*, TR-20, 400-410, R.L. Berglund, ed., Air and Waste Management Association.

Whitten G. and Killus J. (1998) Effect of chemical mechanism uncertainty on airshed model results. Final report prepared for the California Air Resources Board, Technical Support Division, Sacramento, CA, by Systems Applications International, Inc., SYSAPP-97/57, February.

Wilson, J. H., Mullen M. A., Bollman A. D., Thesing K. B. Salhotra M., Divita F., Neumann, J. Price J. C., and DeMocker J. (2008) Emissions projections for the U.S. Environmental Protection Agency Section 812 second prospective Clean Air Act cost/benefit analysis. *J. of Air & Waste Manage. Assoc*. **58**, 657-672.

Winiwarter W. and Rypdal K. (2001) Assessing the uncertainty associated with national greenhouse gas emission inventories: a case study for Austria. *Atmos. Environ.* **35**, 5425-5440.

Winner D.A., Cass G.R., and Harley R.A. (1995) Effect of alternative boundary conditions on predicted ozone control strategy performance: A case study in the Los Angeles area. *Atmos. Environ.* **29**, 3451-3464.

Yang Y.-J., Stockwell W.R., and Milford J.B. (1995) Uncertainties in incremental reactivities of volatile organic compounds. *Environ. Sci. Technol.* **29**, 1336-1345.

Yang Y.-J., Wilkinson J.G., and Russell A.G. (1997) Fast, direct sensitivity analysis of multidimensional photochemical models. *Environ. Sci. Technol.* **31**, 2859-2868.

Yarwood G., Stoeckenius T.E., Heiken J.G., and Dunker A.M. (2003) Modeling weekday/weekend ozone differences in the Los Angeles Region for 1997. *J. Air & Waste Manag. Assoc.* **53**, 864-875.

Zhang F., Bei N., Nielsen-Gammon J.W., Li G., Zhang R., Stuart A., and Aksoy A. (2007) Impacts of meteorological uncertainties on ozone pollution predictability estimated through meteorological and photochemical ensemble forecasts. *J. Geophys. Res.* **112**, D04304, doi:04310.01029/02006JD007429.

Zhao Y. and Frey H.C. (2004) Development of probabilistic emission inventories of air toxics for Jacksonville, Florida, USA. *J. Air & Waste Manag. Assoc.* **54**, 1405-1421.

APPENDIX C | QUALITATIVE UNCERTAINTY SUMMARY TABLES FOR SECOND SECTION 812 PROSPECTIVE ANALYSIS OF THE CLEAN AIR ACT

TABLE C-1. KEY UNCERTAINTIES ASSOCIATED WITH EMISSIONS ESTIMATION

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS	LIKELY SIGNIFICANCE RELATIVE TO KEY UNCERTAINTIES ON NET BENEFITS ESTIMATE[1]
UNCERTAINTIES RELATED TO BASE-YEAR EMISSIONS		
Uncertainties in modeling a counterfactual emissions scenario. Estimating EGU emissions using an alternate counterfactual projection approach yielded increases in air quality impacts and health benefits of 50% relative to the core scenario's IPM-generated estimates.	Underestimate. The IPM-based counterfactual generated substantially lower benefits than the alternative counterfactual scenario specification we tested, which was based on published and readily replicated methodologies. It is possible, however, that other counterfactual specifications would yield lower benefits. It is also possible that the direction of effect might be different for other pollutant source categories where this is no accepted basis to generate an alternative counterfactual scenario estimate.	Potentially major. Analysis confirmed that IPM performs well when estimating with-CAAA emissions, but also highlighted high degree of uncertainty in estimating counterfactual emissions. Similar uncertainties exist for emissions from other emitting sectors. There is no clear way, however, to determine which approach to estimating counterfactual emissions is superior.
Uncertainties in biogenic emissions inputs increase uncertainty in the air quality modeling estimates. Uncertainties in biogenic emissions may be large (± 80%). The biogenic inputs affect the emissions-based VOC/NOx ratio and, therefore, potentially affect the response of the modeling system to emissions changes.	Unable to determine based on current information. The biogenic emissions change overall reactivity, leading to either an underestimate or overestimate of the model's response to emission reductions.	Probably minor. Impacts for ozone and $PM_{2.5}$ results. Both oxidation potential and secondary organic aerosol formation could influence $PM_{2.5}$ formation significantly. However, biogenic emissions are assumed to be unaffected by the CAAA, so this uncertainty should not significantly affect net benefits. Furthermore, ozone benefits contribute only minimally to net benefit projections in this study.
Emissions estimated at the county level (e.g., low-level source and motor vehicle NO_x and VOC emissions) are spatially and temporally allocated based on land use, population, and other surrogate indicators of emissions activity. Uncertainty and error are introduced to the extent that area source emissions are not perfectly spatially or temporally correlated with these indicators.	Unable to determine based on current information.	Probably minor. Potentially major for estimation of ozone, which depends largely on VOC and NO_x emissions; however, ozone benefits contribute only minimally to net benefit projections in this study.

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS	LIKELY SIGNIFICANCE RELATIVE TO KEY UNCERTAINTIES ON NET BENEFITS ESTIMATE[1]
UNCERTAINTIES RELATED TO GROWTH FACTORS		
Economic growth factors used to project emissions are an indicator of future economic activity. These growth factors reflect uncertainty in economic forecasting as well as uncertainty in the link to emissions. IPM projections may be reasonable regionally but may introduce significant biases locally. Also, the Annual Energy Outlook 2005 growth factors do not reflect the recent economic downturn or the volatility in fuel prices since the fall of 2005.	Unable to determine based on current information.	Potentially major. The same set of growth factors are used to project emissions under both the *Without-CAAA* and *With-CAAA* scenarios, mitigating to some extent the potential for significant errors in estimating differences in emissions. Some specific locations may be more significantly influenced. We estimated gross benefits using AEO low-growth and high-growth scenarios and found differences of ±20%. However, due to nonlinearities in the benefits estimation model, we could not reliably determine in what direction over- or underestimating growth might bias net benefits estimates.
The on-road source emissions projections reflect MOBILE6.2 data on the composition of the vehicle fleet. If recent volatility in fuel prices persists or if fuel prices rise significantly (like they did in 2007 and 2008), the motor vehicle fleet may include more smaller, lower-emitting automobiles and fewer small trucks (e.g., SUVs).	Overestimate	Probably minor. Overall, fuel prices affect fleet composition at the margin, and we expect changes in fleet composition to occur gradually over long periods, suggesting that any effect would take several years to fully manifest.
UNCERTAINTIES RELATED TO EMISSIONS CONTROL MODELING		
The *With-CAAA* scenario includes implementation of the Clean Air Mercury Rule (CAMR), which has been vacated, and Clean Air Interstate Rule (CAIR), which was vacated but has since been remanded.	Unable to determine based on current information.	Potentially major. Significance in 2020 will depend on the speed and effectiveness of implementing potential alternatives to CAIR and CAMR. In some areas, emissions reductions are expected to be overestimated, but in other areas, NO_x inhibition of ozone leads to underestimates of ozone benefits (e.g., some urban centers).
VOC emissions are dependent on evaporation, and future patterns of temperature are difficult to predict.	Underestimate. Higher temperatures in the future are more likely than lower temperatures because of climate change, and higher temperature would lead to more emissions in the *without-CAAA* case but controls would keep the *with-CAAA* emissions roughly constant.	Probably minor. The analysis uses meteorological data from 2002 to characterize temperatures during the 30-year period from 1990 to 2020. An acceleration of climate change (warming) could increase emissions but the increase relative to 2002 levels would not likely be significant.

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS	LIKELY SIGNIFICANCE RELATIVE TO KEY UNCERTAINTIES ON NET BENEFITS ESTIMATE[1]
Use of average temperatures (i.e., daily minimum and maximum) in estimating motor-vehicle emissions artificially reduces variability in VOC emissions.	Unable to determine based on current information.	Probably minor. Use of averages will overestimate emissions on some days and underestimate on other days. Effect is mitigated in *With-CAAA* scenarios because of more stringent evaporative controls that are in place by 2000 and 2010.
Uncertainties in the stringency, scope, timing, and effectiveness of *With-CAAA* controls included in projection scenarios.	Unable to determine based on current information.	Probably minor. Future controls could be more or less stringent, widely applicable, or effective than projected. Timing of emissions reductions may also be affected.
The location of the emissions reductions achieved from unidentified measures is uncertain. We currently treat these reductions as if they are achieved from non-point sources, but this may not be correct in all cases.	Unable to determine based on current information.	Probably minor. Impacts from these uncertainties would be localized and would not significantly change the overall net benefit estimate.

1 The classification of each potential source of error reflects the best judgment of the section 812 Project Team. The Project Team assigns a classification of “potentially major” if a plausible alternative assumption or approach could influence the overall monetary benefit estimate by approximately five percent or more; if an alternative assumption or approach is likely to change the total benefit estimate by less than five percent, the Project Team assigns a classification of “probably minor.”

EXHIBIT C-2. KEY UNCERTAINTIES ASSOCIATED WITH COST ESTIMATION

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS	LIKELY SIGNIFICANCE RELATIVE TO KEY UNCERTAINTIES ON NET BENEFITS ESTIMATE[1]
Uncertainty in the maximum per ton costs for local controls to comply with the 8-hour Ozone and $PM_{2.5}$ NAAQS.	Unable to determine based on current information	Probably minor. Our analysis of local controls assumes a maximum cost of $15,000 per ton for local controls implemented to comply with 8-hour Ozone and $PM_{2.5}$ NAAQS requirements.[5] Local areas may implement more costly controls to comply with the NAAQS, but technological innovation may lead to the development of less expensive controls.
Uncertainty in the projected composition of motor vehicle sales and the fuel efficiency of the motor vehicle fleet.	Unable to determine based on current information	Probably minor. We projected the composition of motor vehicle sales and the fuel efficiency of the motor vehicle fleet based on AEO 2005 data. The sensitivity analysis of alternative sales and fuel efficiency projections presented in this report suggests that this uncertainty has a small impact on net benefits.
Uncertainty regarding failure rates for motor vehicle inspections.	Unable to determine based on current information	Probably minor. The repair costs for vehicles that fail emission inspections represent a small fraction of the estimated net benefits of the amendments. The failure rate sensitivity analysis presented in this report suggests that alternative failure rate assumptions could have a large effect on the costs for this component of the CAAA, but only a minor effect on the estimated net benefits of the amendments as a whole.
Costs for some technologies and emissions sectors reflect default assumptions about the rates at which learning affect costs because empirical information is unavailable.	Underestimate	Probably minor. Based on the advice of the Council on Clean Air Compliance Analysis, we used a conservative learning rate of 10 percent for those sectors where no empirical data were available.[2] In contrast, the learning curve literature suggests that the average learning rate is approximately 20 percent, suggesting that learning will reduce costs more than is reflected in the present analysis.[3]

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS	LIKELY SIGNIFICANCE RELATIVE TO KEY UNCERTAINTIES ON NET BENEFITS ESTIMATE[1]
Uncertainties in the economic growth projections that form the basis of the cost analysis.	Unable to determine based on current information	Probably minor. The project team used AEO 2005 economic growth projections, which suggest that the economy will grow at an annual rate of 3.1 percent through 2025.[4] This growth rate is in line with historical GDP growth.
Incomplete characterization of certain indirect costs, such as productivity impacts for regulated industry.	Unable to determine based on current information	Probably minor. The literature on the productivity impacts of the CAAA is unclear with respect to the direction and magnitude of these effects.
Product quality degradation associated with emission control technology.	Unable to determine based on current information	Unable to determine based on current information. Conceptually, the potential for CAAA requirements to affect product quality could result in an underestimate or overestimate of the welfare effects of compliance costs, and therefore an indeterminate effect on net benefits. Unfortunately, few studies exist that address the potential product quality effects of CAAA regulations.
Exclusion of the impact of technological innovation and input substitution on compliance costs.	Underestimate	Probably minor. Minimal information is available on the potential effects of technological innovation on costs. Though input substitution is a potential source of cost savings, the analysis primarily models mature industries and compliance strategies which have been established as least-cost compliance paths. In addition, many regulations, such as RACT, are technology-based and may not allow for much input substitution.
Partial estimation of costs for compliance with the $PM_{2.5}$ NAAQS, due to the unavailability of emission reduction targets for non-attainment areas.	Overestimate	Probably minor. The 2006 $PM_{2.5}$ NAAQS RIA estimates that the incremental costs of residual non-attainment (i.e., costs of additional reductions from unidentified controls needed to reach attainment) are approximately $4.3 billion in 2020, yielding total cost estimates that exceed the estimates presented here by a factor of five or more.[6] However, we estimate that the costs of the $PM_{2.5}$ NAAQS represent less than 5 percent of the net benefits of the amendments.[7]

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS	LIKELY SIGNIFICANCE RELATIVE TO KEY UNCERTAINTIES ON NET BENEFITS ESTIMATE[1]
Uncertainty in the emission reduction estimates used to estimate the costs for select rules.	Unable to determine based on current information	Probably minor. Costs for many rules are not dependent on the corresponding emissions reductions (e.g., fuel sulfur limits, tailpipe standards, etc.)
Exclusion of the impact of economic incentive provisions, including banking, trading, and emissions averaging provisions.	Underestimate	Probably minor. Economic incentive provisions can substantially reduce costs, but the major economic programs for trading of sulfur and nitrogen dioxide emissions are reflected in the analysis.
Potential for overestimation biases in engineering cost estimates.	Underestimate	Probably minor. A study by Harrington, Morgenstern, and Nelson (1999) evaluated the accuracy of EPA and OSHA estimates of 25 *ex ante* regulatory cost estimates relative to *ex post* studies of actual costs, and concluded that initial cost estimates by EPA tend to overstate costs. The source of these biases include a built-in conservative bias, inaccuracies in estimating the size of the affected universe, the effect of learning on reducing costs, the effect of innovation on reducing costs, and cost-reducing features of regulatory design. Some of these factors are discussed elsewhere in this table. The magnitude of these biases varies substantially, but in no case would we expect the overall impact to exceed five percent of overall net benefits.

1 The classification of each potential source of error reflects the best judgment of the section 812 Project Team. The Project Team assigns a classification of "potentially major" if a plausible alternative assumption or approach could influence the overall monetary benefit estimate by approximately five percent or more; if an alternative assumption or approach is likely to change the total benefit estimate by less than five percent, the Project Team assigns a classification of "probably minor."

2 U.S. Environmental Protection Agency Science Advisory Board, EPA-SAB-COUNCIL-ADV-07-002, "Benefits and Costs of Clean Air Act – Direct Costs and Uncertainty Analysis", Advisory Letter, June 8, 2007. Available at http://www.epa.gov/sab/pdf/council-07-002.pdf.

3 For an analysis of the learning rates estimated in the empirical literature, see John M. Dutton and Annie Thomas, "Treating Progress Functions as a Managerial Opportunity," *Academy of Management Review*, Vol 9, No. 2, 1984.

4 U.S. Department of Energy, Energy Information Administration, *Annual Energy Outlook 2005*, February 2005.

5 The Project Team uses this maximum unit cost value in two ways. First, the Project Team assumes that local areas would not implement identified controls costing more than $15,000 per ton. Second, the Project Team assumes a cost of $15,000 per ton for unidentified controls.

6 U.S. Environmental Protection Agency. *Regulatory Impact Analysis for the Particulate Matter NAAQS*. October, 2006.

7 For detailed estimates of the costs of $PM_{2.5}$ NAAQS compliance, see E.H. Pechan and Associates, Inc. and Industrial Economics, Inc., *Direct Cost Estimates for the Clean Air Act Second Section 812 Prospective Analysis*, prepared for U.S. EPA, March 2009.

TABLE C-3. KEY UNCERTAINTIES ASSOCIATED WITH AIR QUALITY MODELING

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS	LIKELY SIGNIFICANCE RELATIVE TO KEY UNCERTAINTIES ON NET BENEFITS ESTIMATE*
Unknown meteorological biases in the 12-km western and 36-km MM5 domains due to the lack of model performance evaluations.	Unable to determine based on current information.	Probably minor. Other evaluations using 2002 and similar meteorology and CMAQ have shown reasonable model performance. Although potentially major affects on nitrate results in western areas with wintertime $PM_{2.5}$ problems.
Known metrological biases in the 12-km eastern MM5 domain. MM5 has a cold bias during the winter and early spring, and has a general tendency to underestimate the monthly observed precipitation. MM5's under prediction was greatest in the fall and least in the spring months.	Unable to determine based on current information.	Probably minor. These biases would likely influence $PM_{2.5}$ formation processes, which was modeled on the 36-km domain.
Secondary organic aerosol (SOA) chemistry. CMAQ version 4.6 has known biases (underprediction) in SOA formation.	Underestimate.	Possibly major. The modeling system underpredicts SOA, which has both biogenic and anthropogenic components. Reductions in NOx can reduce both biogenic and anthropogenic SOA and reductions in VOC will reduce anthropogenic SOA. Since both of these precursors are significantly impacted by the CAAA, there may be large benefits from SOA related reductions that are not currently captured by the modeling system.
The CMAQ modeling relies on a modal approach to modeling $PM_{2.5}$ instead of a sectional approach. The modal approach is effective in modeling sulfate aerosol formation but less effective in modeling nitrate aerosol formation than the sectional approach.	Unable to determine based on current information.	Probably minor in the eastern U.S. where annual $PM_{2.5}$ is dominated by sulfate. Potentially major in some western U.S. areas where $PM_{2.5}$ is dominated by secondary nitrate formation.

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS	LIKELY SIGNIFICANCE RELATIVE TO KEY UNCERTAINTIES ON NET BENEFITS ESTIMATE*
Limited model performance evaluation of CMAQ for 2002.	Unable to determine based on current information.	Probably minor. While a comprehensive model evaluation was not completed, the overall results of the CMAQ runs for the Second Prospective were assessed using AMET, and bias and error statistics were within acceptable ranges. Further, our application of the MATS procedure provides further assurance that air quality results used in the subsequent health assessments are consistent with available monitor data.
Ozone modeling relies on a 12-km grid, suggesting NO_x inhibition of ambient ozone levels may be under-represented in some urban areas. Grid resolution may affect both model performance and response to emissions changes.	Unable to determine based on current information.	Probably minor. Though potentially major ozone results in those cities with known NO_x inhibition, ozone benefits contribute only minimally to net benefit projections in this study. Grid size affects chemistry, transport, and diffusion processes, which in turn determine the response to changes in emissions, and may also affect the relative benefits of low-elevation versus high-stack controls.
Emissions estimated at the county level (e.g., low-level source and motor vehicle NO_x and VOC emissions) are spatially and temporally allocated based on land use, population, and other surrogate indicators of emissions activity. Uncertainty and error are introduced to the extent that area source emissions are not perfectly spatially or temporally correlated with these indicators.	Unable to determine based on current information.	Probably minor. Potentially major for estimation of ozone, which depends largely on VOC and NO_x emissions; however, ozone benefits contribute only minimally to net benefit projections in this study.

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS	LIKELY SIGNIFICANCE RELATIVE TO KEY UNCERTAINTIES ON NET BENEFITS ESTIMATE*
Use of MATS relative response factors to calculate changes in $PM_{2.5}$	Indeterminate	Probably minor. Using MATS, air quality modeling results were projected in a “relative” sense. In this approach, the ratio of future year model predictions to base year model predictions are used to adjust ambient measured data up or down depending on the relative (percent) change in model predictions for each location. The use of ambient data as part of the calculation helps to reduce uncertainties in the future year predictions, especially if the absolute model concentrations are over-predicted or under-predicted.
Modeling artifacts created by changes in emissions inventory estimation methods between the 1990 inventories used for the *without-CAAA* scenario and the 2002 inventories used for the *with-CAAA* scenarios were mitigated through application of adjustment factors for primary PM from non-EGU point sources, and for the certain subsectors of area sources, in the *without-CAAA* case. Application of these adjustments may result in overestimated or underestimated changes in primary PM contributions to ambient concentrations for these particular sources.	Unable to determine based on current information.	Probably minor. While primary PM can make a significant contribution to ambient $PM_{2.5}$ in some locations, secondarily formed fine particles dominate the estimates for ambient concentration change in this analysis. In addition, the effect of the inventory adjustments was to significantly reduce the differentials between the control and counterfactual scenarios, implying any residual error is more likely to reflect an underestimation bias than an overestimation bias, particularly since the non-EGU primary PM reductions were adjusted to a scenario differential of zero.

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS	LIKELY SIGNIFICANCE RELATIVE TO KEY UNCERTAINTIES ON NET BENEFITS ESTIMATE*
Adjustments to take account of processes that remove fugitive dust from the ambient air at or close to the source of emissions, owing to the effect of forests, vegetation, and urban structures on fugitive dust. Analysis of the chemical species collected by ambient air samplers suggests that the modeling process may overestimate $PM_{2.5}$ from fugitive dust sources by as much as an order of magnitude, if not adjusted for this effect. The Project Team incorporated adjustments post-CMAQ modeling but prior to use of PM air quality estimates in subsequent steps of the analysis.	Unable to determine based on current information.	Probably minor. If adjustment factors had been applied as part of the CMAQ modeling, evidence suggests the entrainment effect would have been adequately accounted for. The largely linear processes of direct PM emissions to air quality suggest that our *post-hoc* adjustment should also be adequate to account for this factor. Further assurance that this factor has been accounted for is our application of the MATS monitor calibration procedure, which provides a speciated calibration to ensure better agreement between air quality modeling results and comparable monitor data, and the fact that the adjustment applies to both scenarios, further mitigating the impact of this source of uncertainty.

* The classification of each potential source of error is based on those used in the First Prospective Analysis. The classification of “potentially major” is used if a plausible alternative assumption or approach could influence the overall monetary benefit estimate by approximately 5% or more; if an alternative assumption or approach is likely to change the total benefit estimate by less than 5%, the classification of “probably minor” is used.

TABLE C-4. KEY UNCERTAINTIES ASSOCIATED WITH HUMAN HEALTH EFFECTS MODELING

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS ESTIMATE	MAGNITUDE OF IMPACT ON NET BENFITS ESTIMATE	DEGREE OF CONFIDENCE
UNCERTAINTIES RELATED TO PREMATURE MORTALITY BENEFITS ESTIMATES			
Analysis assumes a causal relationship between PM exposure and premature mortality based on strong epidemiological evidence of a PM/mortality association. However, epidemiological evidence alone cannot establish this causal link.	Overestimate	Potentially major. PM/mortality effects are the largest contributor to the net benefits estimate. If the PM/mortality relationship is not causal, it would lead to a significant overestimation of net benefits.	High. The assumption of causality is suggested by the epidemiologic and toxicological evidence and is consistent with current practice in the development of a best estimate of air pollution-related health benefits. At this time, we can identify no basis to support a conclusion that such an assumption results in a known or suspected overestimation bias.
Analysis assumes a causal relationship between ozone exposure and premature mortality based on strong epidemiological and experimental evidence of an ozone/mortality association.	Overestimate	Probably minor. Ozone mortality effects are a large contributor to the net benefits estimate, but total monetized ozone mortality benefits remain less than five percent of total net benefits. If the ozone mortality relationship is not causal, it would lead to an overestimation of net benefits.	Medium. Several epidemiological studies provide strong evidence for associations between ozone and mortality. This data is supported by human and animal experimental studies that provide suggestive evidence for plausible mechanisms. Overall, the evidence is highly suggestive, but additional research is needed to more fully establish underlying mechanisms.

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS ESTIMATE	MAGNITUDE OF IMPACT ON NET BENFITS ESTIMATE	DEGREE OF CONFIDENCE
It is possible that the PM/mortality relationship is modified by socioeconomic status (SES).	Unable to determine based on current information. Consideration of both the Pope and Laden studies avoids the possible underestimation effect from the ACS cohort, owing to the demographics of that study population, and the possible overestimation bias associated with the more limited geographic scope of the Harvard Six-Cities cohort.	Potentially major. Sensitivity analyses reported in this chapter indicate the high sensitivity of benefits results to the choice of the PM/mortality C/R function.	Medium. Studies have found effect modification of the PM/mortality effect by SES, as assessed through education attainment (Krewski et al., 2000). However, this effect is likely to affect only the Pope et al. estimate. Our inclusion of both the Pope et al. and Laden et al. (which does includes a more diverse population) helps account for the possible significance of this uncertainty.
Exposure misclassification due to reliance on ambient monitoring data to estimate $PM_{2.5}$ exposures rather than measuring personal exposures.	Underestimate. Concentrations measured at central site monitors may not accurately reflect exposure experienced by the population due to variation in ambient concentrations over space within a geographic area, incomplete penetration of ambient pollution into homes and workplaces, patterns of population activity and indoor sources that can contribute significantly to individual $PM_{2.5}$ exposures. Reducing exposure error can result in stronger associations between pollutants and health effects than generally observed in studies having less exposure detail.	Potentially major. Recent analyses reported in Krewski et al. (2009) demonstrate the relatively significant effect that this source of uncertainty can have on effect estimates.	High. The results from Krewski et al. (2009) and Jerrett et al. (2005) suggest that exposure error may underestimate effect estimates (PM ISA).

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS ESTIMATE	MAGNITUDE OF IMPACT ON NET BENFITS ESTIMATE	DEGREE OF CONFIDENCE
Exclusion of C-R functions from short-term exposure studies in PM mortality calculations.	Underestimate	Potentially major. PM/mortality is the top contributor to the net benefits estimate. If short-term functions contribute substantially to the overall PM-related mortality estimate, then the net benefits could be underestimated.	Medium. Long-term PM exposure studies likely capture a large part of the impact of short-term peak exposure on mortality; however, the extent of overlap between the two study types is unclear.
Assumption that PM-related mortality occurs over a period of 20 years following the critical PM exposure. Analysis assumes that 30% of mortality reductions in the first year, 50% over years 2 to 5, and 20% over the years 6 to 20 after the reduction in $PM_{2.5}$	Unable to determine based on current information	Potentially major. PM/mortality is the largest contributor to monetary benefits. Our quantitative sensitivity analysis indicated that alternative plausible cessation lag structures could alter the benefits estimate between 23% lower to 16% higher than the primary estimate.	Medium. Recent epidemiological studies (e.g., Schwartz, 2008) have shown that the majority of the risk occurs within 2 years of reduced exposure. However, our default lag assumes 43% of mortality reductions would occur within the first 2 years. The evidence directly informing the cessation lag structure is somewhat limited, but the current lag is supported by the Council HES.
Assumption of a linear, no-threshold model for PM and ozone mortality	Overestimate	Probably minor. Although consideration for alternative model forms (Krewski et al., 2009) does suggest that different models can impact risk estimates to a certain extent, generally this appears to be a moderate source of overall uncertainty.	High. The current scientific literature does not support a population-based threshold, which consistently shows effects down to the lowest measureable levels. If a threshold does exist, it is likely below the range of concentrations of regulatory interest.

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS ESTIMATE	MAGNITUDE OF IMPACT ON NET BENFITS ESTIMATE	DEGREE OF CONFIDENCE
Mortality health impact did not include pollutants other than PM or ozone.	Unable to determine based on current information	Probably minor. If other criteria pollutants correlated with PM contribute to mortality, that effect may be captured in the PM estimate. This uncertainty does make it difficult to disaggregate avoided mortality benefits by pollutant.	High. PM and ozone are the two pollutants most strongly linked to mortality in the epidemiological literature. It is likely that we've captured the majority of mortality benefits due to criteria pollutants in our analysis.
Pooling with equal weights of ozone mortality incidence estimates to present a primary estimate.	Unable to determine based on current information	Probably minor. Pooling with equal weights provides a central estimate of ozone mortality benefits, but it is not clear that the six ozone mortality incidence studies should be combined in this manner. Relying on a particular single study or another combination of studies may result in significantly different estimated benefits from ozone reductions. However, ozone-related avoided mortality benefits are a minor contributor to total monetized benefits.	Medium. All six studies are associated with different strengths and limitation. No single study has emerged as solely suitable to support a primary estimate. Therefore, a pooled estimate provides a central estimate of the available literature.

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS ESTIMATE	MAGNITUDE OF IMPACT ON NET BENFITS ESTIMATE	DEGREE OF CONFIDENCE
No cessation lag was used for ozone mortality.	Overestimate	Probably minor. If there is a time lag between changes in ozone exposure and the total realization of changes in health effects then benefits occurring in the future should be discounted. The use of no lag assumes that all mortality benefits are realized in the year of the exposure change and therefore no discounting occurs. This may lead to an overestimate of benefits.	High. Due to the use of short-term studies of ozone mortality, use of a no lag structure is appropriate and supported by the Council HES.
UNCERTAINTIES RELATED TO APPLICATION OF C-R FUNCTIONS			
Application of C-R relationships only to those subpopulations matching the original study population.	Underestimate	Probably minor. The C-R functions for several health endpoints (including PM-related premature mortality) were applied only to subgroups of the U.S. population (e.g. adults 30+) and thus may underestimate the whole population benefits of reductions in pollutant exposures. However, the background incidence rates for these age groups are likely low and therefore would not contribute many additional cases.	High. The baseline mortality and morbidity rates for PM-related health effects are significantly lower in those under the age of 30 (other than neonates).

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS ESTIMATE	MAGNITUDE OF IMPACT ON NET BENFITS ESTIMATE	DEGREE OF CONFIDENCE
Application of regionally derived C-R estimates to entire U.S.	Unable to determine based on current information	Probably minor. This is likely to affect morbidity estimates rather than mortality, as mortality estimates are based on studies that include multiple cities. Since morbidity is not as large of a contributor to overall benefits, this is not likely to have a large impact on net benefits.	Medium. The differences in the expected changes in health effects calculated using different underlying studies can be large. If differences reflect real regional variation, applying individual C-R functions throughout the U.S. could result in considerable uncertainty in health effect estimates.
UNCERTAINTIES RELATED TO HEALTH VALUATION			
Use of a Value-of-a-Statistical-Life (VSL) estimate based on a Weibull distribution of 26 studies	Unable to determine based on current information	Potentially major. Mortality valuation generally dominates monetized benefits.	Medium. The VSL used in this analysis is based on 26 labor market and stated preference studies published between 1974 and 1991. Although there are many more recent studies, including meta-analyses, sensitivity analyses reported above suggest that these alternative sources generate results that are close to the estimates used in the analysis.
Use of cost of illness (COI) estimates to value some morbidity endpoints	Underestimate	Probably minor. Mortality valuation generally dominates monetized benefits; therefore specific estimates used to generate morbidity benefits likely would not have a large impact on net benefits.	Low. Morbidity benefits such as hospital admissions and heart attacks are calculated using COI estimates, which some studies have shown are generally half as much as WTP to avoid the illness. However, WTP estimate are currently not available for all health endpoints.

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS ESTIMATE	MAGNITUDE OF IMPACT ON NET BENFITS ESTIMATE	DEGREE OF CONFIDENCE
Benefits transfer for mortality risk valuation, including differences in age, income degree of risk aversion, the nature of the risk, and treatment of latency between mortality risks presented by PM/ozone and the risks evaluated in the available economic studies.	Unable to determine based on currently available information	Potentially major. The mortality valuation step is clearly a critical element in the net benefits estimate, so any uncertainties can have a large effect.	Medium. Information on the combined effect of these known biases is relatively sparse, and it is therefore difficult to assess the overall effect of multiple biases that work in opposite directions. However, our VSL estimate is based on a distribution of the results of 26 individual studies, which cover a range of characteristics.
Inability to value some quantifiable morbidity endpoints, such as impaired lung function.	Underestimate	Probably minor. Reductions in lung function are a well-established effect, based on clinical evaluations of the impact of air pollutants on human health, and the effect would be pervasive, affecting virtually every exposed individual. However, the lack of a clear symptomatic presentation of the effect, however, could limit individual WTP to avoid lung function decrements.	Low. There currently is no evidence to determine the monetary value of the benefits of avoided lung function reductions.

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS ESTIMATE	MAGNITUDE OF IMPACT ON NET BENFITS ESTIMATE	DEGREE OF CONFIDENCE
UNCERTAINTIES IN FORECASTED DATA SUPPORTING HEALTH EFFECTS ESTIMATES			
Uncertainty in projecting baseline incidence rates	Both	Probably minor. The magnitude varies with the health endpoint. Mortality baseline incidence is at the county level and projected for 5-year increments. Morbidity baseline incidence has varying spatial resolution for year 2000 only.	Medium. The county-level baseline incidence and population estimates were obtained from databases where the relative degree of uncertainty is low. The baseline data for other endpoints are not location specific (e.g., those taken from studies) and therefore may not accurately represent the actual location-specific rates.
Income growth adjustments	Both	Potentially major. Income growth increases willingness-to-pay valuation estimates, including mortality, over time.	Medium It is difficult to forecast future income growth, owing to unpredictability of future business and employment cycles. These can have a substantial effect on short term growth rate projections, although over longer periods economic growth rates have tended to converge. The use of data from AEO 2005, however, omits the effect of the most recent economic downturn.

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS ESTIMATE	MAGNITUDE OF IMPACT ON NET BENFITS ESTIMATE	DEGREE OF CONFIDENCE
Population projections	Both	Probably minor. The magnitude varies with the health endpoint. Mortality baseline incidence is at the county level and projected for 5-year increments. Morbidity baseline incidence has varying spatial resolution for year 2000 only.	Medium. The county-level baseline incidence and population estimates were obtained from databases where the relative degree of uncertainty is low. The baseline data for other endpoints are not location-specific (e.g., those taken from studies) and therefore may not accurately represent the actual location-specific rates.
Income growth adjustments	Both	Potentially major. Income growth increases willingness-to-pay valuation estimates, including mortality, over time.	Medium. It is difficult to forecast future income growth, owing to unpredictability of future business and employment cycles. These can have a substantial effect on short-term growth rate projections, although over longer periods, economic growth rates have tended to converge. The use of data from AEO 2005, however, omits the effect of the most recent economic downturn.

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS ESTIMATE	MAGNITUDE OF IMPACT ON NET BENFITS ESTIMATE	DEGREE OF CONFIDENCE
Population projections	Both	Probably minor. The demographics of population forecasting are relatively well-established, however migration estimates are quite uncertain, particularly for specific locations. Overall, we believe that population projections are not likely to vary more than 5 percent at the national level.	Medium. Population projections cannot adequately account for future population migration due to catastrophic events. Projected population and demographics may not well represent future-year population and demographics.
OTHER UNCERTAINTIES			
Variation in effect estimates reflecting differences in $PM_{2.5}$ composition	Unable to determine based on current information	Unable to determine based on current information	Medium. Epidemiology studies examining regional differences in $PM_{2.5}$-related health effects have found differences in the magnitude of those effects. While these may be the result of factors other than composition (e.g., different degrees of exposure misclassification), composition remains one potential explanatory factor.
Very limited quantification of health effects associated with exposure to air toxics.	Underestimate	Probably minor. Studies have found air toxics cancer risks to be orders of magnitude lower than those of criteria pollutants.	N/A Current data and methods are insufficient to develop (and value) national quantitative estimates of the health effects of these pollutants.

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS ESTIMATE	MAGNITUDE OF IMPACT ON NET BENFITS ESTIMATE	DEGREE OF CONFIDENCE
CAAA fugitive dust controls implemented in PM non-attainment areas would reduce lead exposures by reducing the re-entrainment of lead particles emitted prior to 1990. This analysis does not estimate these benefits.	Underestimate	Probably minor. The health and economic benefits of reducing lead exposure can be substantial (e.g., see section 812 Retrospective Study Report to Congress). However, most additional fugitive dust controls implemented under the *with-CAAA* scenario (e.g., unpaved road dust suppression, agricultural tilling controls, etc.) tend to be applied in relatively low population areas.	N/A

TABLE C-5. KEY UNCERTAINTIES ASSOCIATED WITH ECOLOGICAL EFFECTS ESTIMATION

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS	LIKELY SIGNIFICANCE RELATIVE TO KEY UNCERTAINTIES ON NET BENEFITS ESTIMATE*
Incomplete coverage of ecological effects identified in existing literature, including the inability to adequately discern the role of air pollution in multiple stressor effects on ecosystems. Examples of categories of potential ecological effects for which benefits are not quantified include: reduced eutrophication of estuaries, reduced acidification of soils, reduced bioaccumulation of mercury and dioxins in the food chain.	Underestimate	Potentially major. The extent of unquantified and unmonetized benefits is largely unknown, but the available evidence suggests the impact of air pollutants on ecological systems may be widespread and significant.
Incomplete geographic scope of recreational fishing benefits associated with reduced lake acidification analysis due to case study approach.	Underestimate	Potentially major. As a case study limited to the Adirondack region of New York State, the estimated benefits to recreational fishing reflect only a portion of the overall benefits of reduced acidification on this service flow, but based on the magnitude of effects in the Adirondacks, the national estimate is nonetheless likely to be less than five percent of total benefits.
Incomplete assessment of long-term bioaccumulative and persistent effects of air pollutants.	Underestimate	Potentially major. Little is currently known about the longer-term effects associated with the accumulation of toxins in ecosystems. What is known suggests the potential for major impacts. Future research into the potential for threshold effects is necessary to establish the ultimate significance of this factor.
Omission of the effects of nitrogen deposition as a nutrient with beneficial effects.	Overestimate	Probably minor. Although nitrogen does have beneficial effects as a nutrient in a wide range of ecological systems, nitrogen in excess also has significant and in some cases persistent detrimental effects that are also not adequately reflected in the analysis.

POTENTIAL SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR NET BENEFITS	LIKELY SIGNIFICANCE RELATIVE TO KEY UNCERTAINTIES ON NET BENEFITS ESTIMATE*
Use of CMAQ model to estimate air pollutant deposition levels.	Unable to determine. As part of a performance evaluation of CMAQ, EPA compared model predictions for some forms of deposition relevant to this analysis (wet SO2, NOx, and ammonium) to observed deposition data).** The evaluation indicated that CMAQ overpredicted some forms of deposition and underpredicted others. The relative accuracy of the model's predictions varied seasonally and geographically.	Probably minor. The Adirondack lake acidification analysis uses deposition estimates as inputs, but they are calibrated to lake-level monitoring data, and the monetized benefits estimates for that component are a small part of the overall net benefits. We also use the CMAQ deposition estimates to generate maps that highlight the relative distribution of deposition for various air pollutants across the U.S. With respect to net impacts, the extent to which the forms of deposition and geographic areas that are overpredicted by those that re underpredicted is unknown.

* The classification of each potential source of error reflects the best judgment of the section 812 Project Team. The Project Team assigns a classification of "potentially major" if a plausible alternative assumption or approach could influence the overall monetary benefit estimate by approximately five percent or more; if an alternative assumption or approach is likely to change the total benefit estimate by less than five percent, the Project Team assigns a classification of "probably minor."

** See U.S. EPA, Office of Air Quality Planning and Standards, Emissions Analysis and Monitoring Division, Air Quality Modeling Group. CMAQ Model Performance Evaluation Report for 2001: Updated March 2005. CAIR Docket OAR-2005-0053-2149.