CHAPTER 1 | INTRODUCTION

Section 812 of the Clean Air Act Amendments of 1990 (CAAA) required the U.S. Environmental Protection Agency (EPA) to perform periodic, comprehensive analyses of the total costs and total benefits of programs implemented pursuant to 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 was completed in 1997. Section 812 also required performance of prospective cost-benefit analyses, the first of which was completed in 1999. The prospective analyses address the incremental costs and benefits of the CAAA. The 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 CAAA 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 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 using statistical sampling to analyze the impact of upstream uncertainties in emissions and air quality modeling inputs on the criteria pollutant concentration outputs. Both the NAS 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. While the NAS 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 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.

1.2 OVERVIEW OF UNCERTAINTY ANALYSIS APPROACH

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

1.3.1 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.

1.3.2 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 particulate matter 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.

1.3.3 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 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

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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 applying alternative estimates of the income elasticity also being conducted in many of the Agency's benefits analyses.

1.3.4 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

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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 concentration-response 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 Response Surface Model (RSM) for CMAQ, a less resource intensive meta-model of CMAQ used to rapidly approximate PM concentrations.[1]

The bottom box in Exhibit 1-1 lists additional offline research and analysis 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 important analytical elements or key 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 an Appendix to this report.

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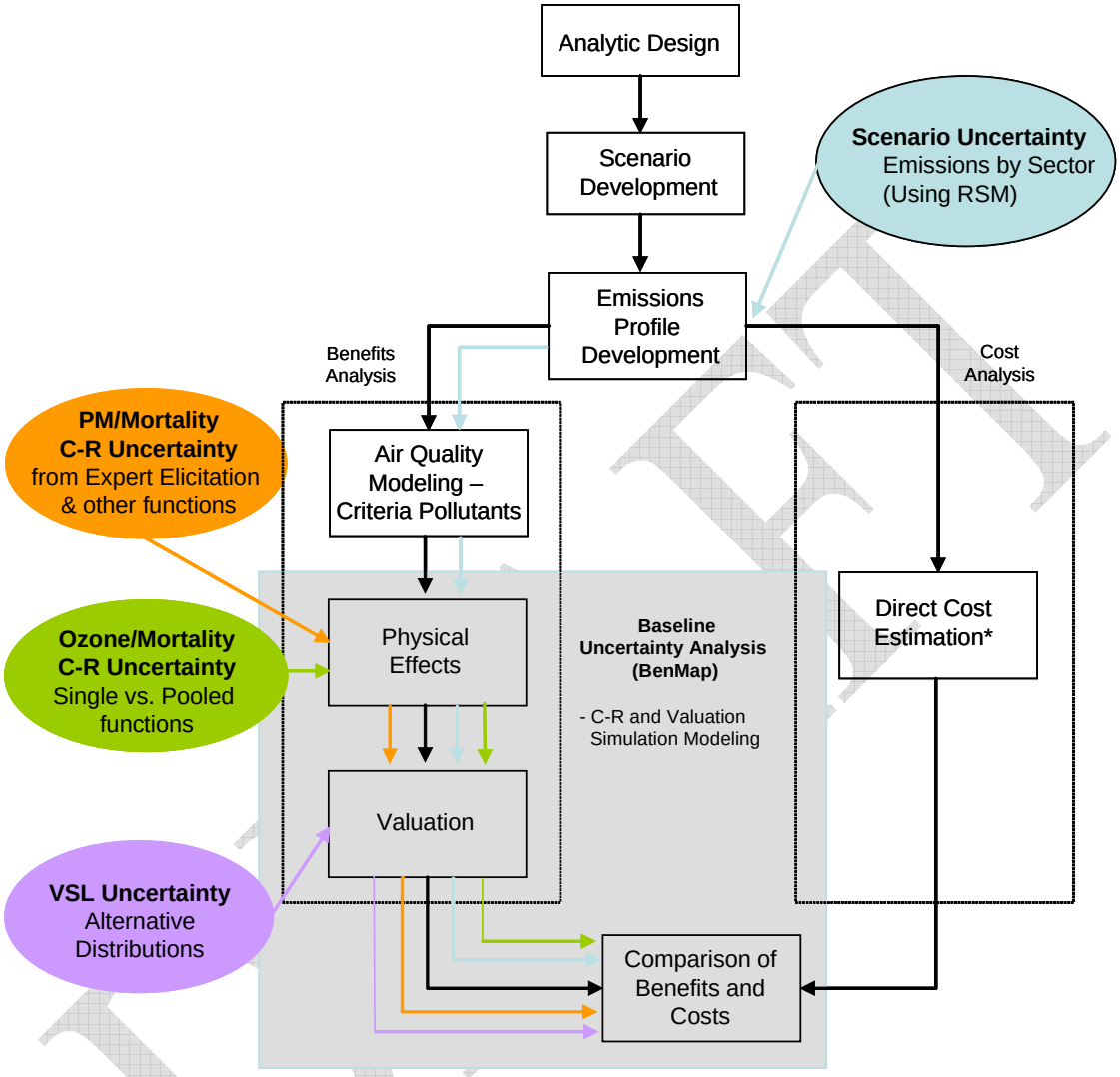
[1] Model performance issues led to a Project Team decision to abandon a similar effort using a RSM for ozone based on CAM-X. A CMAQ-based ozone RSM is not yet available.

EXHIBIT 1-1 IEC 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 three 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.

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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.
Visibility	RESERVED FOR THIS DRAFT	RESERVED FOR THIS DRAFT	RESERVED FOR THIS DRAFT
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).

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 benefit and cost reports for the overall second prospective effort. 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 EPA Science Advisory Board 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.

With the completion and review of the benefits and uncertainty analyses, the Agency will prepare an integrated report for the entire project. The integrated report will address each of the major analytic components, and present comparisons of benefits and costs for each of the target years, as well as integrate the implications of uncertainty analyses that characterize confidence in these results.

1.5 ORGANIZATION OF DOCUMENT

The remainder of the document is split into nine chapters:

- **Chapter 2: Direct Cost-Related Uncertainty** – [This chapter is reserved for this draft.]
- **Chapter 3: Emissions and Air Quality Modeling Uncertainty** – [This chapter is reserved for this draft.]
- **Chapter 4: Concentration-Response Function Uncertainty** – This chapter provides estimates of CAAA-related avoided deaths resulting from application of alternative concentration-response functions for both particulate matter and ozone.
- **Chapter 5: Differential Toxicity of PM Components** – This chapter provides our assessment of potential approaches to account for differential toxicity of particulate matter components.
- **Chapter 6: Particulate Matter/Mortality Cessation Lag** – This chapter explores uncertainty in the assumption of the cessation lag between CAAA-related 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 is reserved for this draft.]
- **Chapter 9: Visibility** – [This chapter is reserved for this draft.]
- **Chapter 10: Conclusions** – [This chapter is reserved for this draft.]

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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. 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. 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), plus the 2008 National Research Council (NRC) review.[1] The Project Team assessed the sensitivity of the Second Prospective 812 estimates of PM- and ozone-related mortality incidence to C-R function uncertainty by substituting alternative

[1] 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.

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.

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.

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.

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.

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.

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.

PM and ozone C-R functions in BenMAP and reanalyzing benefits with the core scenario CMAQ air quality grids for each target year.[2]

4.2 SELECTION OF ALTERNATIVE C-R FUNCTIONS

4.2.1 PARTICULATE MATTER CONCENTRATION-RESPONSE FUNCTIONS

The Project Team generated two alternative sets of estimates reflecting alternative C-R functions, in addition to the primary estimate based on Pope et al. (2002).[3] The first set of results is based on the Six Cities Cohort study follow-up (Laden et al., 2006).[4] The second consists of the results from the *Expanded Expert Judgment Assessment of the Concentration-Response Relationship Between $PM_{2.5}$ Exposure and Mortality* (the PM EE study).[5] EPA conducted the PM EE study to improve the characterization of uncertainty in the C-R relationship between changes in $PM_{2.5}$ exposures and mortality, using formally elicited expert judgments. The goal of the study was to elicit from a sample of health experts probabilistic distributions describing uncertainty in estimates of the reduction in mortality among the adult U.S. population resulting from reductions in ambient annual average $PM_{2.5}$ levels. These distributions were obtained using a formal interview protocol based on methods designed to elicit subjective expert judgments. The EE study involved personal interviews with 12 peer-nominated health experts who have conducted research on the relationship between $PM_{2.5}$ exposures and mortality. The results of the full-scale study consist of 12 individual distributions for the coefficient or slope of the C-R function relating changes in annual average $PM_{2.5}$ exposures to annual, adult all-cause mortality. Each individual expert's C-R function uncertainty distribution is displayed in Exhibit 4-1. We generated individual estimates of CAAA-related avoided mortality incidence based on the C-R functions provided by each of the 12 experts that participated in the EE study.

[Placeholder: The Project Team is exploring approaches for combining the expert distributions from the EE study; details of that effort will be presented separately to the SAB.]

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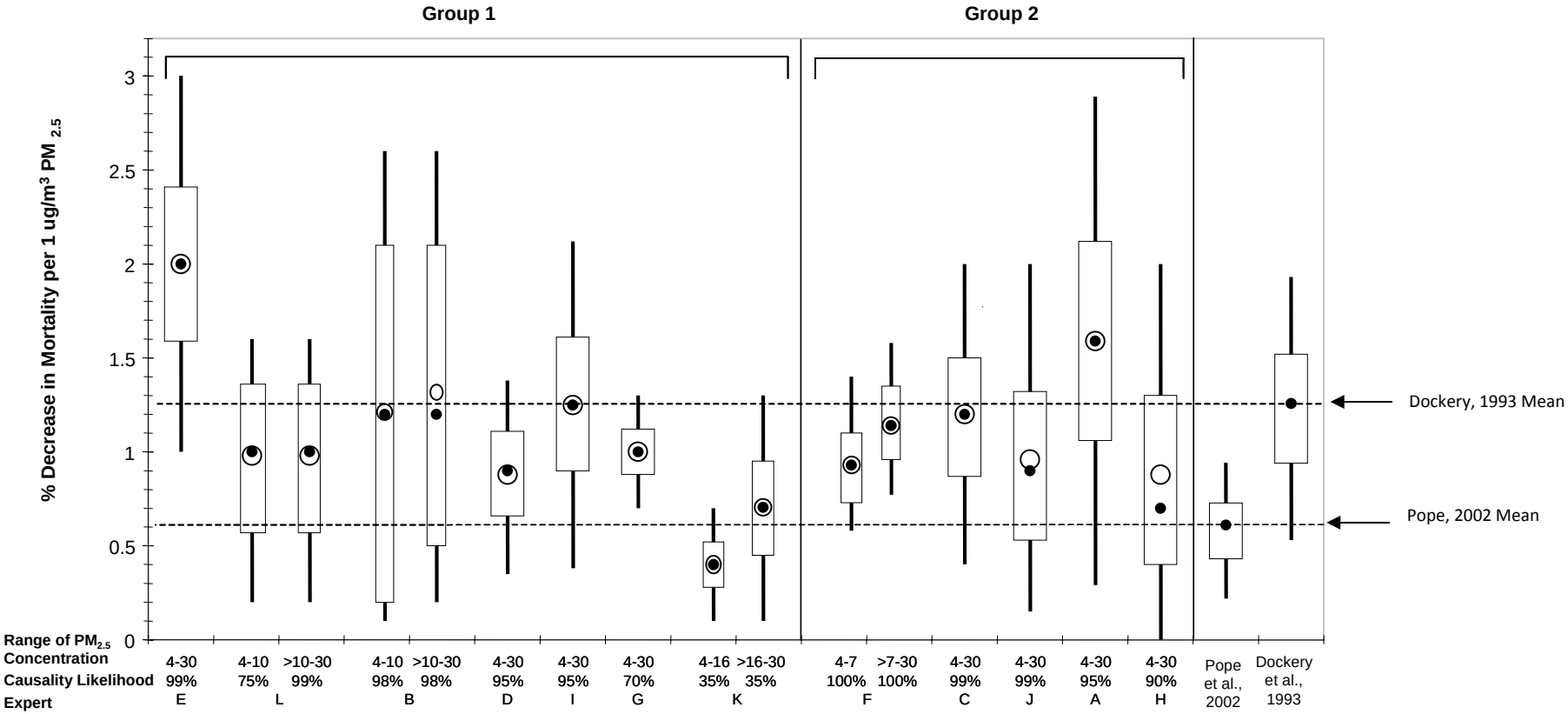
[2] The alternate C-R functions used in our analysis are programmed into BenMAP, as explained in the BenMAP manual in Appendices F and G (Abt Associates, Inc. (2008). BenMAP User's Manual. Prepared for the U.S. EPA's Office of Air Quality Planning and Standards, Research Triangle Park, NC. September).

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

[4] 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.

[5] 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.

EXHIBIT 4-1 UNCERTAINTY DISTRIBUTIONS FOR THE PM2.5-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

We generated results for six alternative ozone/mortality C-R functions. These results are individual estimates of CAAA-related avoided mortality incidence based on six ozone/mortality studies: Schwartz, 2005; Bell et al., 2004; Huang et al., 2005; Ito et al., 2005; Levy et al., 2005; and Bell et al., 2005.[6] Three of these studies report C-R functions based on non-accidental mortality (Ito et al., 2005; Bell et al., 2004; and Schwartz et al., 2005), two are based on all-cause mortality (Bell et al., 2005 and Levy et al., 2005) and one is based on cardiopulmonary mortality (Huang et al., 2005). Three of the studies are meta-analyses (Ito et al., 2005; Levy et al., 2005; Bell et al., 2005) and three are multi-city estimates derived from the National Morbidity, Mortality, and Air Pollution Study (NMMAPS) (Schwartz, 2005; Bell et al., 2004; Huang et al., 2005). The primary estimate used to quantify CAAA-related reductions in ozone-related mortality in the 812 benefits report is a pooled estimate of Bell et al. (2004) and Schwartz (2005) using inverse variance weighting.

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 4-2 presents changes in mortality incidence for all three target years (2000, 2010, and 2020) associated with the primary C-R function (Pope et al., 2002) and the alternative C-R functions (Laden et al., 2006 and the EE study results). Exhibit 4-3 is a box plot presenting the mean values from each of the alternative C-R functions, as well as the 5th and 95th percentile results, using the mortality results for 2020. Below is a summary of the key results:

- Our mean primary estimate (using Pope et al., 2002) of annual avoided deaths due to CAAA-related changes in $PM_{2.5}$ in each of the three target years is 68,000 in 2000; 100,000 in 2010; and 140,000 in 2020.

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[6] 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.

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.

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.

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.

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.

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.

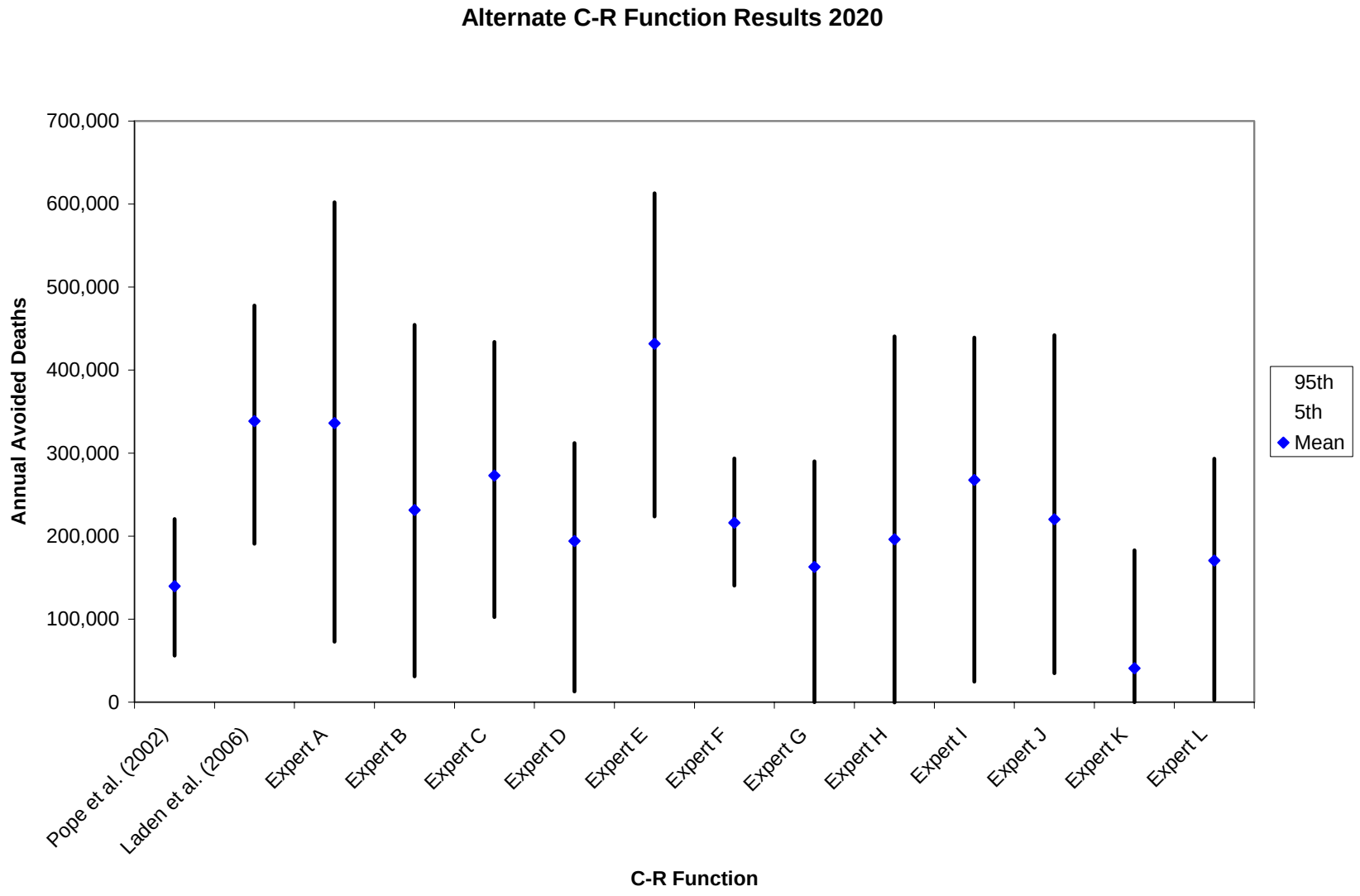
- The mean benefits estimates generated from the Laden et al. (2006) study are roughly 150 percent higher than the primary estimate based on Pope et al. (2002), due to the difference in the magnitude of the relative risks (RRs) from these two studies (Laden reports a RR of 1.15 and Pope reports an RR of 1.06 for a 10 $\mu g/m^3$ change in $PM_{2.5}$).
- The mean estimates of annual avoided deaths due to the CAAA generated from the PM expert elicitation results vary by expert and range between 20,000 and 220,000 for 2000; 30,000 and 320,000 for 2010; and 41,000 and 430,000 for 2020.
- Overall, mean mortality incidence estimates using the alternative C-R functions range from within approximately -70 percent to +220 percent of the primary estimate.
- As shown in Exhibit 4-3, 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 Expert F's distribution. The spread of the primary estimate (Pope et al, 2002), which only estimates statistical uncertainty, is slightly greater than that of Expert F's distribution. 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.

EXHIBIT 4-2 ALTERNATIVE C-R FUNCTION MORTALITY INCIDENCE RESULTS[1]

MORTALITY C-R FUNCTION	2000			2010			2020		
	PERCENTILE 5	MEAN	PERCENTILE 95	PERCENTILE 5	MEAN	PERCENTILE 95	PERCENTILE 5	MEAN	PERCENTILE 95
Pope et al. (2002) (Default)	**27,000**	**68,000**	**110,000**	**41,000**	**100,000**	**160,000**	**56,000**	**140,000**	**220,000**
Laden et al. (2006)	94,000	170,000	240,000	140,000	250,000	360,000	190,000	340,000	480,000
Expert A	35,000	170,000	310,000	53,000	250,000	450,000	73,000	340,000	600,000
Expert B	15,000	120,000	240,000	23,000	180,000	350,000	31,000	230,000	450,000
Expert C	50,000	140,000	220,000	75,000	200,000	320,000	100,000	270,000	430,000
Expert D	6,200	96,000	150,000	9,300	140,000	230,000	13,000	190,000	310,000
Expert E	110,000	220,000	310,000	160,000	320,000	460,000	220,000	430,000	610,000
Expert F	71,000	110,000	150,000	110,000	160,000	220,000	140,000	220,000	290,000
Expert G	0	80,000	140,000	0	120,000	210,000	0	160,000	290,000
Expert H	0	97,000	220,000	0	140,000	330,000	0	200,000	440,000
Expert I	12,000	130,000	220,000	18,000	200,000	330,000	25,000	270,000	440,000
Expert J	17,000	110,000	220,000	25,000	160,000	330,000	35,000	220,000	440,000
Expert K	0	20,000	90,000	0	30,000	130,000	0	41,000	180,000
Expert L	1,200	87,000	150,000	1,900	130,000	220,000	2,600	170,000	290,000

Note:
1. Incidence Results are rounded to two significant figures.

EXHIBIT 4-3 BOX-PLOT OF 90 PERCENT CONFIDENCE BOUNDS FOR ALTERNATIVE PM C-R FUNCTION RESULTS IN 2020



4.3.2 EFFECTS OF ALTERNATIVE OZONE CONCENTRATION-RESPONSE FUNCTIONS

Exhibit 4-4 presents changes in mortality incidence for all three target years (2000, 2010, and 2020) associated with the primary C-R function (pooling of Bell et al. (2004) and Schwartz (2005)) and the alternative C-R functions for ozone. Exhibit 4-5 is a box plot presenting the mean incidence values from the primary and alternative C-R functions, as well as the 5th and 95th percentile results. Below is a summary of the key results:

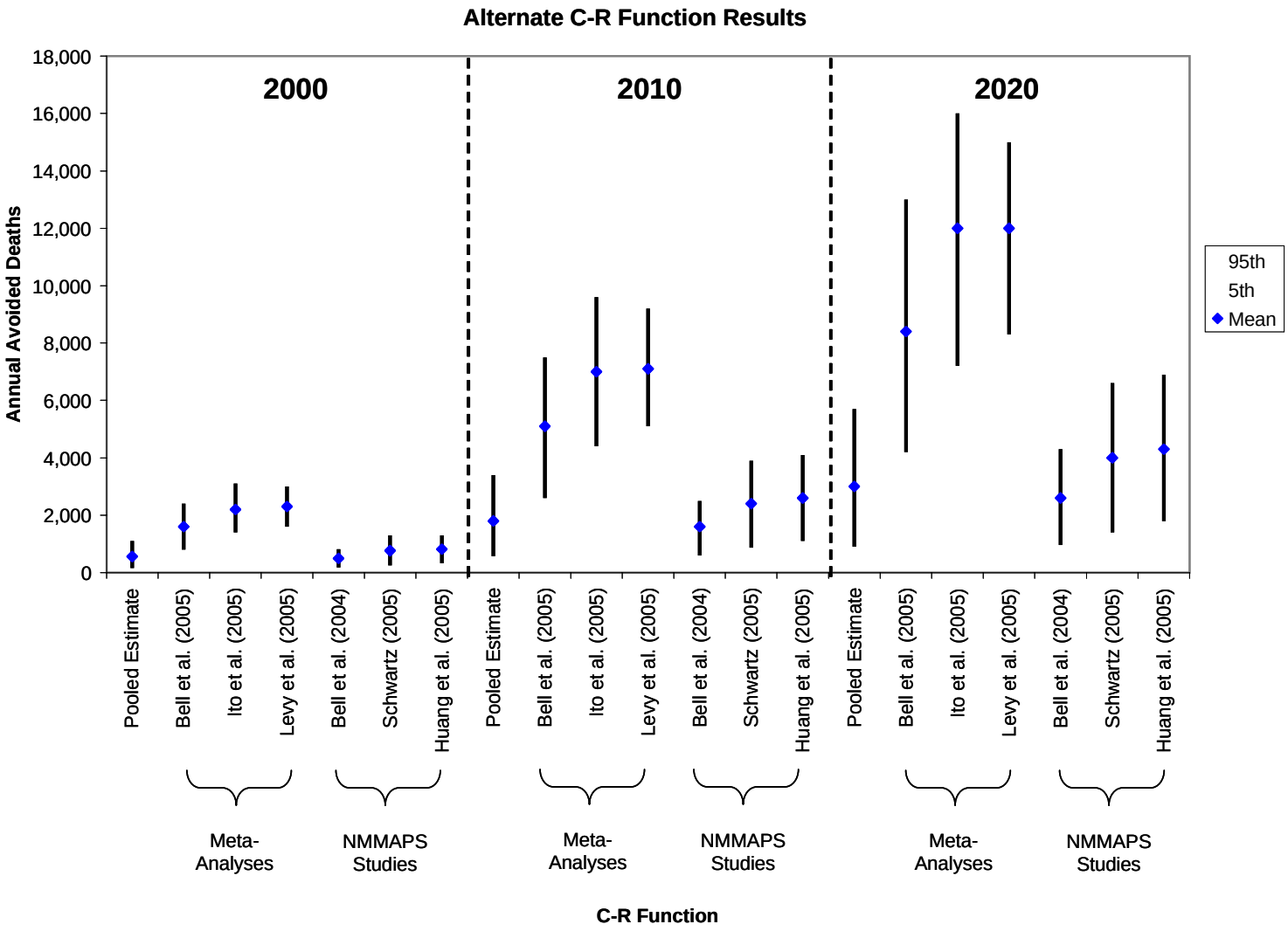
- Our mean primary estimate (using the pooling of Bell et al. (2004) and Schwartz (2005)) of annual avoided deaths due to CAAA-related changes in ozone in each of the three target years is 560 in 2000; 1,800 in 2010; and 3,000 in 2020.
- The mean benefits estimates generated from the Levy et al. (2005) meta-analysis are the greatest, at approximately 300 percent greater than the primary estimate, though these are very similar to, and in some cases identical to, the Ito et al. (2005) meta-analysis estimates. The mean benefits estimates generated from the Bell et al. (2004) NMMAPS study are the lowest (approximately 11 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 NMMAPS-based studies (Schwartz, 2005; Bell et al., 2004; Huang et al., 2005).
- As shown in Exhibit 4-5, the spread of the confidence bounds of the alternative C-R function estimates incidence results vary, with the largest spread found in the distributions provided by Ito et al. (2005) and Bell et al. (2005), and the smallest spread associated with Bell et al. (2004).

EXHIBIT 4-4 ALTERNATIVE C-R FUNCTION MORTALITY INCIDENCE RESULTS FOR OZONE[1]

MORTALITY C-R FUNCTION	2000			2010			2020		
	PERCENTILE 5	MEAN	PERCENTILE 95	PERCENTILE 5	MEAN	PERCENTILE 95	PERCENTILE 5	MEAN	PERCENTILE 95
Pooling of Bell et al. (2004) and Schwartz (2005) (Primary Estimate)	**160**	**560**	**1,100**	**570**	**1,800**	**3,400**	**900**	**3,000**	**5,700**
META-ANALYSES									
Bell et al. (2005)	800	1,600	2,400	2,600	5,100	7,500	4,200	8,400	13,000
Ito et al. (2005)	1,400	2,200	3,100	4,400	7,000	9,600	7,200	12,000	16,000
Levy et al. (2005)	1,600	2,300	3,000	5,100	7,100	9,200	8,300	12,000	15,000
NMMAPS STUDIES									
Bell et al. (2004)	180	500	820	600	1,600	2,500	960	2,600	4,300
Schwartz (2005)	250	760	1,300	870	2,400	3,900	1,400	4,000	6,600
Huang et al. (2005)	330	820	1,300	1,100	2,600	4,100	1,800	4,300	6,900

Notes:
1. Incidence results are rounded to two significant figures.

EXHIBIT 4-5 BOX-PLOT OF 90 PERCENT CONFIDENCE BOUNDS FOR ALTERNATIVE C-R FUNCTION RESULTS FOR OZONE



CHAPTER 5 | DIFFERENTIAL TOXICITY OF PM COMPONENTS[1]

5.1 INTRODUCTION

In the current 812 prospective analysis, EPA estimates 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 Science Advisory Board (SAB) 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 functionally equivalent to the same unit reduction in sulfate concentrations in California in 2020. These and other limitations are discussed in more detail below.

[1] 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.

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 SAB 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.[2]

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).[3] 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).[4] 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.[5]

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

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[2] 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.

[3] 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)

[4] 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.

[5] Franklin M, Zeka A, Schwartz J. 2007. Association between PM2.5 and all-cause and specific-cause mortality in 27 US communities. J Expo Sci Environ Epidemiol. Vol. 17(3):279-87.

component) appear unlikely. Further, any spatial variations in the PM C-R function may 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 SAB 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.

EPA's SAB 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."[6]

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."[7]

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[6] 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.

[7] *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 particulate matter 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).[8,9] Of note, some of the above-mentioned 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.[10] 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.

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

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

[10] Bell, M.L. et al., 2007. Spatial and Temporal Variation in PM2.5 Chemical Composition in the United States for Health Effects Studies. Environmental Health Perspectives. Vo. 115(7): 989-995.

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 NRC in their report entitled "Research Priorities for Airborne Particulate Matter" indicated that:

> "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."[11]

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.[12] 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.[13] 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

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

[12] 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.

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

$\mu g/m^3$ 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, 2008).[14,15] 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).[16] However, a multi-city study focusing on hospital admissions found no associations between sulfate and either respiratory or cardiovascular admissions (Bell et al., 2009).[17] 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).[18,19,20]

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).[21,22] 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

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[14] 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.

[15] 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.

[16] Franklin, M. et al., 2008. The Role of Particle Composition on the Association Between PM2.5 and Mortality. Epidemiology. Vol. 19(5): 680-689.

[17] 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.

[18] 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.

[19] 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.

[20] 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.

[21] 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.

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

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.[23,24]

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."[25] 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).[26,27]

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

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[23] 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.

[24] 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.

[25] 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.

[26] 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.

[27] 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.

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).[28,29,30] A recent study of 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).[31] 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).[32] 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).[33] 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).[34,35] EC and OC showed effects in a

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[28] 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.

[29] 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.

[30] 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.

[31] 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.

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

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

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

[35] 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.

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).[36] 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).[37] 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 with cardiovascular admissions (Bell et al., 2009).[38] 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).[39,40,41,42]

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).[43] 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).[44] 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.

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

[37] 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.

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

[39] 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.*

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

[41] 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.

[42] 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.

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

[44] *Ibid.*

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).[45,46,47,48,49,50,51] However, these studies suffer from a number of 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).[52,53,54] 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.

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[45] 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.

[46] 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.

[47] 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.

[48] 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.

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

[50] 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.

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

[52] 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.

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

[54] 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.

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).[55] 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.[56] 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.[57] Franklin et al. (2008) determined that $PM_{2.5}$ mortality C-R functions were higher when the mass contained more aluminum, arsenic, and nickel.[58] Bell et al. (2009) found that communities with higher levels of nickel and vanadium had elevated C-R functions for PM-related hospitalizations, a finding supported by others (Lippmann et al., 2006).[59,60]

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).[61] 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).[62,63,64] These particles have been found to contain high levels of iron, copper, nickel, lead and zinc. In

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

[56] 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.

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

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

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

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

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

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

[63] 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.

[64] 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.

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). [65,66,67]

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."[68]

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 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). [69,70] These studies typically relate daily concentrations of PM components and gaseous co-pollutants to underlying source types

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[65] 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.

[66] 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.

[67] 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.

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

[69] 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.

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

(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.[71] This term would not be directly applicable to the 812 prospective analysis, whose study period post-dates the phaseout 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 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).[72] Thus, while these studies have tremendous value in interpreting the epidemiological literature, they are not likely to be practical for health benefits analysis.

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

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

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). [73]
- 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 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).

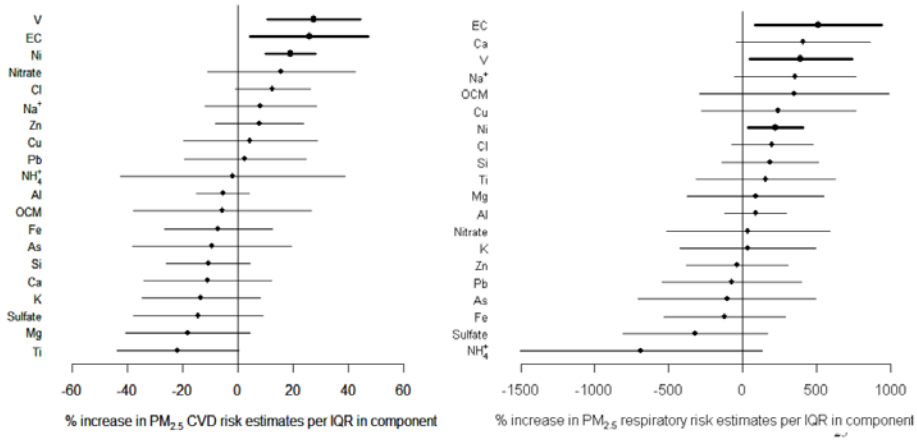
[73] *Ibid.*

- 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). [74] Figure 3 from this paper is replicated below, as it helps to illustrate the potential and pitfalls of such investigations.



[74] 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 $\mu g/m^3$ (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 $\mu g/m^3$ for EC and 0.001 $\mu g/m^3$ 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 Monte Carlo 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). [75] 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

[75] 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.

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 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 Science Advisory Board (SAB) advice, 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 particulate matter (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) are step functions that have been used by EPA in previous benefits analyses. The third cessation lag model follows a new structure that 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 main 812 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:[1] (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

[1] 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.

Weibull distribution configured to match (undefined) expected low, most likely, and expected high values. The EPA requested comment from the SAB Health Effects Subcommittee (HES) on these three approaches.

In a March 2004 advisory report, the SAB HES provided an in-depth assessment of the cessation lag issue and the three approaches put forth by the EPA.[2] 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 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, the EPA identified an alternative lag structure that assumes 20 percent of the total 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 SAB 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.[3] 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 SAB recommended that the EPA use a 20-year lag structure, where 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. 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

[2] 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.

[3] 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.[4] 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 SAB HEES. The 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 which 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 SAB 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 SAB 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.[5] The authors of this study developed a smooth function lag based on the assumption 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

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[4] 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.

[5] 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.

cohort studies as well as intervention studies as described further below. In addition, its use is consistent with the SAB'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:

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

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:

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

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

$$\Delta M = ERR \cdot t - \frac{ERR}{k} + \frac{ERR}{k} \exp^{-kt} . \qquad (3)$$

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).[6,7] We standardized the published relative risk estimates from these two studies to represent a 10 $\mu g/m^3$ increase in PM_{10}.[8]

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

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

[7] 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.

[8] 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.

"Dublin Coal Ban" study).[9] This study found a 1.6 percent decrease in mortality per 10 μg/m^3 PM_{10} over a six-year period, resulting in a ΔM of 0.1 percent-years. 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).[10] This study reported a 2.1 percent decrease in mortality per 10 μg/m^3 PM_{10} over a 13-month period (corresponding to a ΔM of 0.02 percent-years).[11]

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 SAB'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).[12,13,14] 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).[15,16]

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.

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[9] 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.

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

[11] 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 μg/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.

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

[13] 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).

[14] 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.

[15] 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.

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

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]
0.10	Smoking Cessation Literature[3]	
0.15	ACS[4]	Dublin Coal Ban
0.37	Six Cities	Utah Valley[5]
1.24	ACS	Utah Valley

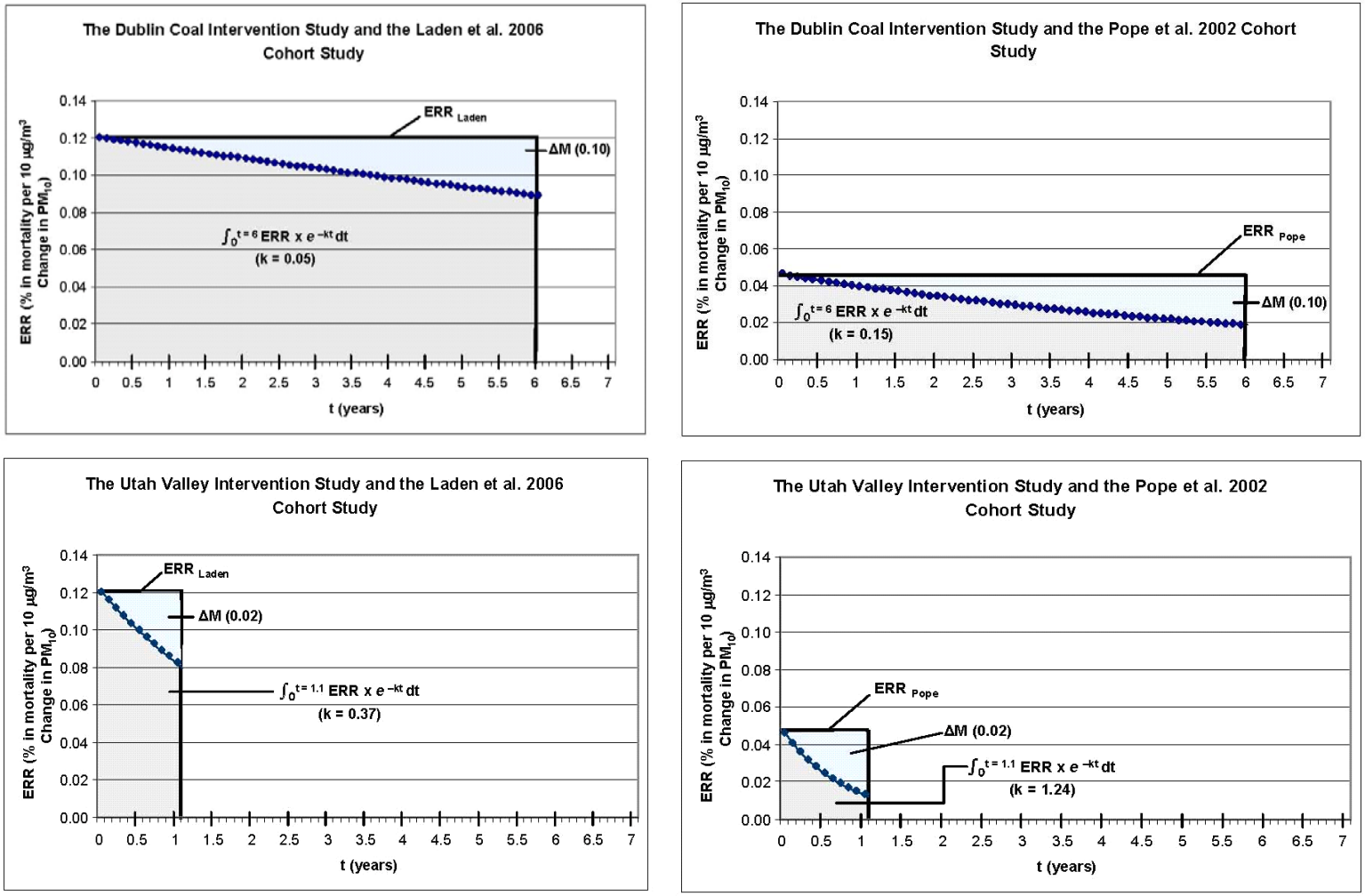
[1] Laden, F., et al. (2006). Reduction in fine particulate air pollution and mortality – Extended follow-up of the Harvard Six Cities Study. *Am J Respir Crit Care Med* 173: 667-672.
[2] Clancy, L., P. Goodman, et al. (2002). Effect of air-pollution control on death rates in Dublin, Ireland: an intervention 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 *ERR*s 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 *ERR*s 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 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.

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



The spreadsheet uses the estimates of avoided deaths from BenMAP generated from the use of the 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.[17]

6.3 EFFECT OF ALTERNATIVE CESSATION LAG STRUCTURES

The exponential decay function that we employed as a new alternative lag structure relies upon 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. Since the primary PM benefits estimate in the main 812 report relies upon the C-R function derived from the Pope et al., 2002 cohort study, we first present the uncertainty resulting from applying the two step functions and the exponential functions derived from the Pope cohort study to the mortality incidence results generated with the Pope et al. C-R function. We next present the monetized benefits resulting from applying the two step functions and the exponential decay functions derived from the Laden study to the mortality incidence results generated with the Laden C-R function. We also compare the results of applying the exponential decay function lag based on the smoking literature to both the Pope and Laden incidence results.

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

Exhibits 6-3 and 6-4 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 6-3 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 for the three target years (2000, 2010, and 2020) using each of the alternative cessation lag structures. We present below a summary of the key results of our cessation lag analysis of the Pope mortality reductions:

- Application of the default, 20-year distributed lag results in a net present economic value (discounted back to the target year with a 5 percent discount rate) of our mean primary estimate of avoided deaths due to CAAA-related changes in $PM_{2.5}$ of $460 billion in 2000, $730 billion in 2010 and $1,100 billion in 2020 (in 2006$).
- The five-year distributed lag valuation results are roughly 7 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

[17] 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.

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 Pope and the Dublin Coal Ban study (k = 0.15), the economic value decreases 10 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 due to the discount rate. 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 92 percent of avoided mortality occurs within the first year. These results are 13 percent higher than the default lag assumption in 2020. Use of the k value derived from the smoking cessation literature (k = 0.10) results in a monetary benefits estimate that is approximately 20 percent lower than the 20-year distributed lag in 2020.
- Assuming no lag, and therefore no discounting of VSL, results in an increase in benefits 13 percent above the default, 20-year distributed lag in 2020.

EXHIBIT 6-3 ALTERNATE CESSATION LAGS – ANNUAL DEATHS (POPE ET AL., 2002)

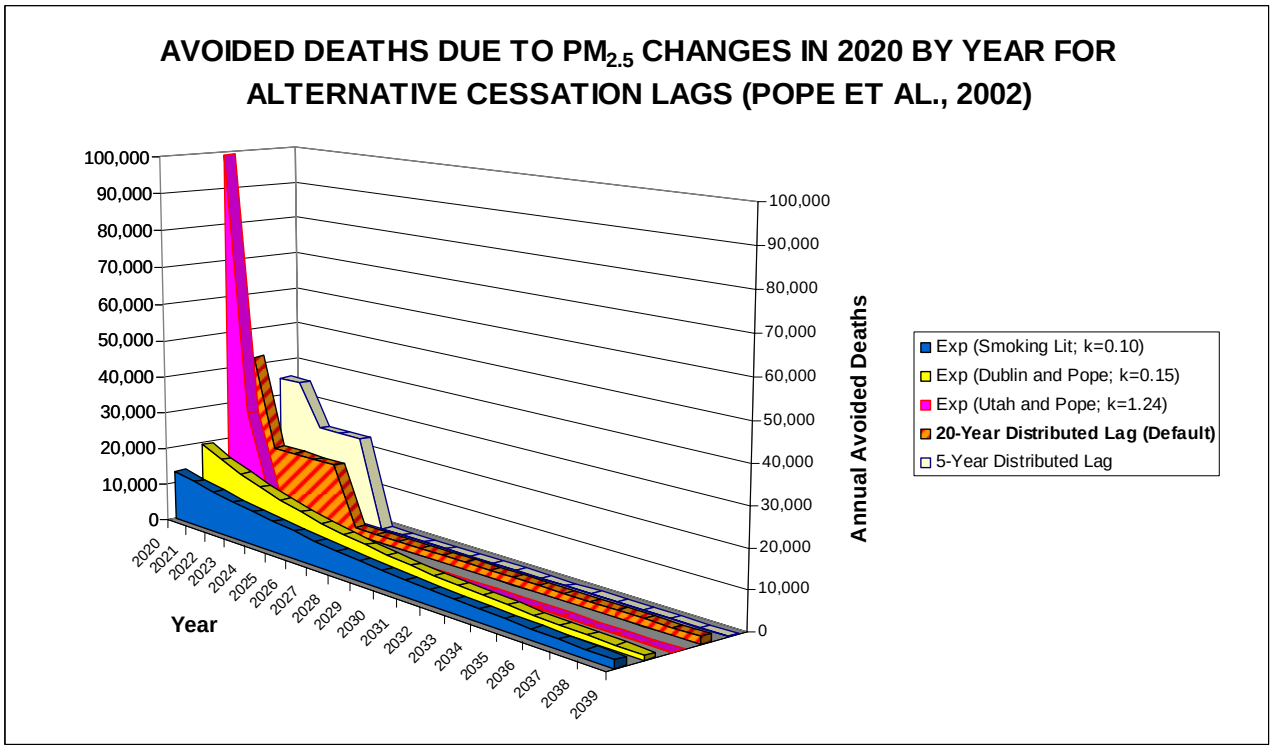


EXHIBIT 6-4 ALTERNATE CESSATION LAGS - CUMULATIVE DEATHS (POPE ET AL., 2002)

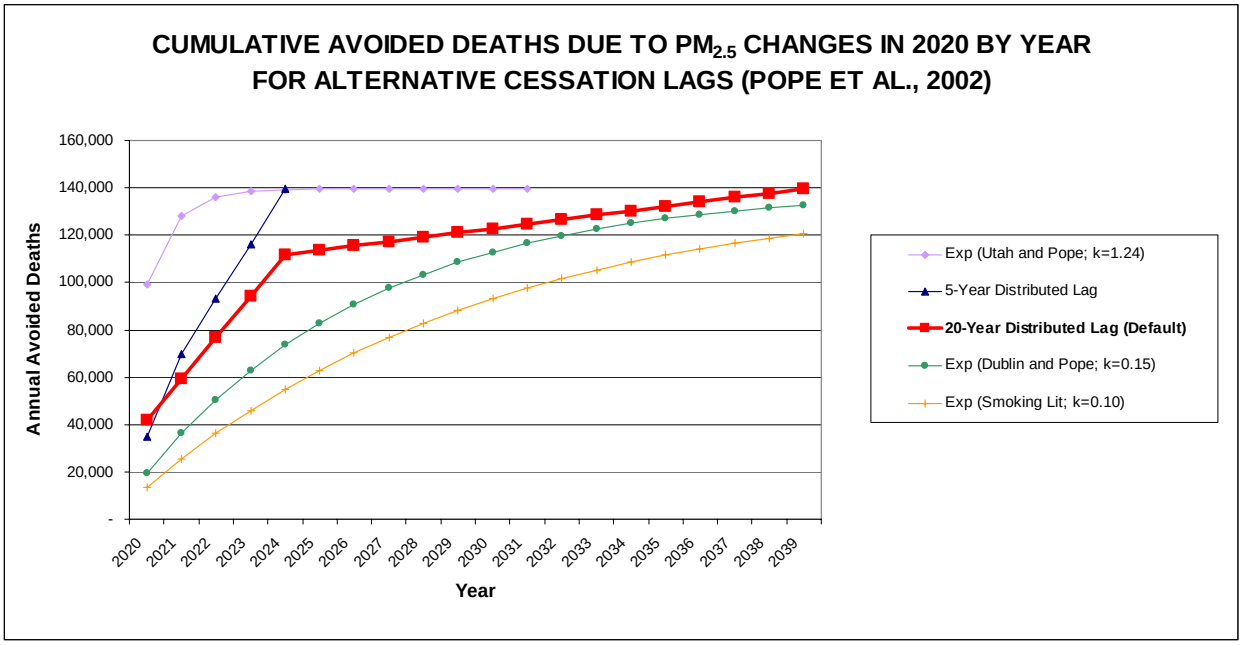


EXHIBIT 6-5 MEAN VALUATION RESULTS USING ALTERNATIVE LAG STRUCTURES - POPE ET AL., 2002

MORTALITY CESSATION LAG	MEAN VALUATION (MILLION 2006$)		
	2000	2010	2020
20 Year Distributed Lag (Default)	**$460,000**	**$730,000**	**$1,100,000**
5 Year Distributed Lag	$490,000	$780,000	$1,200,000
Smooth Function, k = 0.10	$380,000	$600,000	$890,000
Smooth Function, k = 0.15	$420,000	$670,000	$990,000
Smooth Function, k = 1.24	$520,000	$820,000	$1,200,000
No Lag, No Discounting	$520,000	$830,000	$1,200,000

6.3.2 RESULTS BASED ON LADEN ET AL., 2006

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 Laden 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 mean valuation results for the three target years (2000, 2010, and 2020) using each of the alternative cessation lag structures. We present below a summary of the key results of our cessation lag analysis of the Laden mortality reductions:

- Application of the default, 20-year distributed lag results in net present economic value (discounted back to the target year with a 5 percent discount rate) applied to the Laden-derived estimate of avoided deaths due to CAAA-related changes in $PM_{2.5}$ of $1,100 billion in 2000, $1,800 billion in 2010 and $2,600 billion in 2020 (in 2006$).
- As with 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 decreases 35 percent from the default in 2020. Application of this time constant spreads the avoided deaths over a very long time period, causing the economic value to be reduced significantly due to discounting. Applying the k value derived from Laden and the Utah Valley study (k = 0.37) results in valuation estimates that are only 8 percent higher than the default value in 2020. This lag is fairly similar to the 20-year distributed lag in terms of how the avoided deaths accrue over time, as seen in Exhibit 6-7.
- In general, application of the Laden cohort study results in a large increase in the total number of avoided deaths (150 percent greater) over the default Pope estimate. However, applying the smooth function lag structure with the k values derived from Laden slows the accrual of avoided deaths over time. Therefore, these benefits are valued with more highly discounted VSLs. Applying the 0.05 value for k to the Laden mortality reductions, for instance, results in monetized benefits that are only 55 percent greater than the Primary Estimate which uses Pope et al., 2002 and the default lag.

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

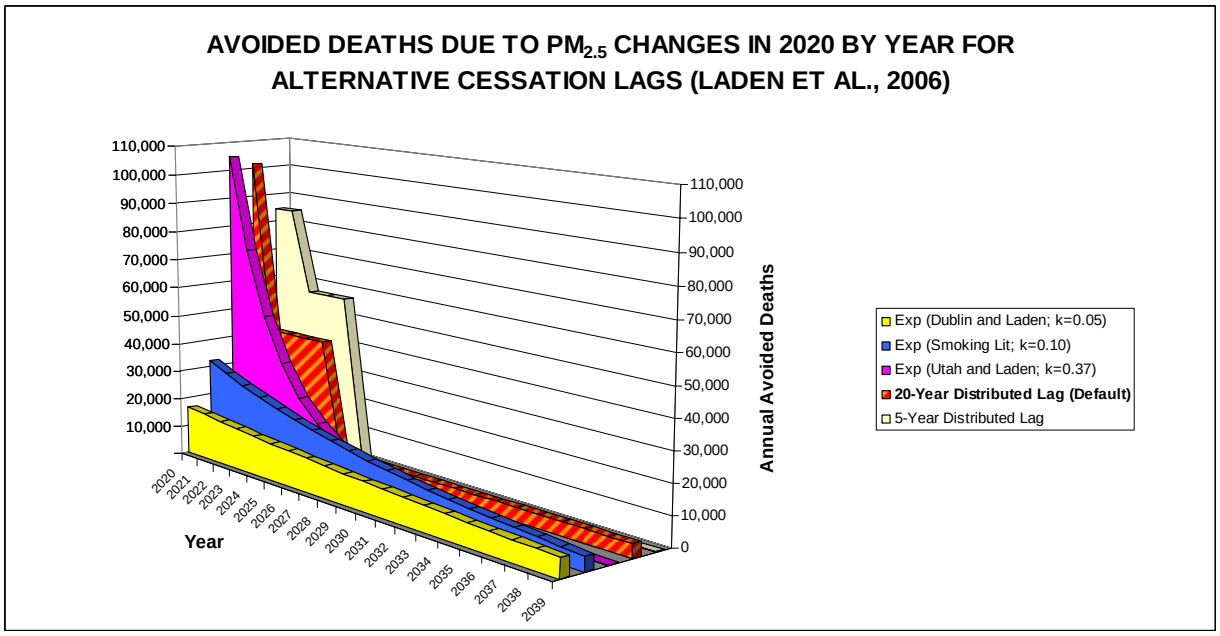


EXHIBIT 6-7 ALTERNATE CESSATION LAGS - CUMULATIVE DEATHS (LADEN ET AL., 2006)

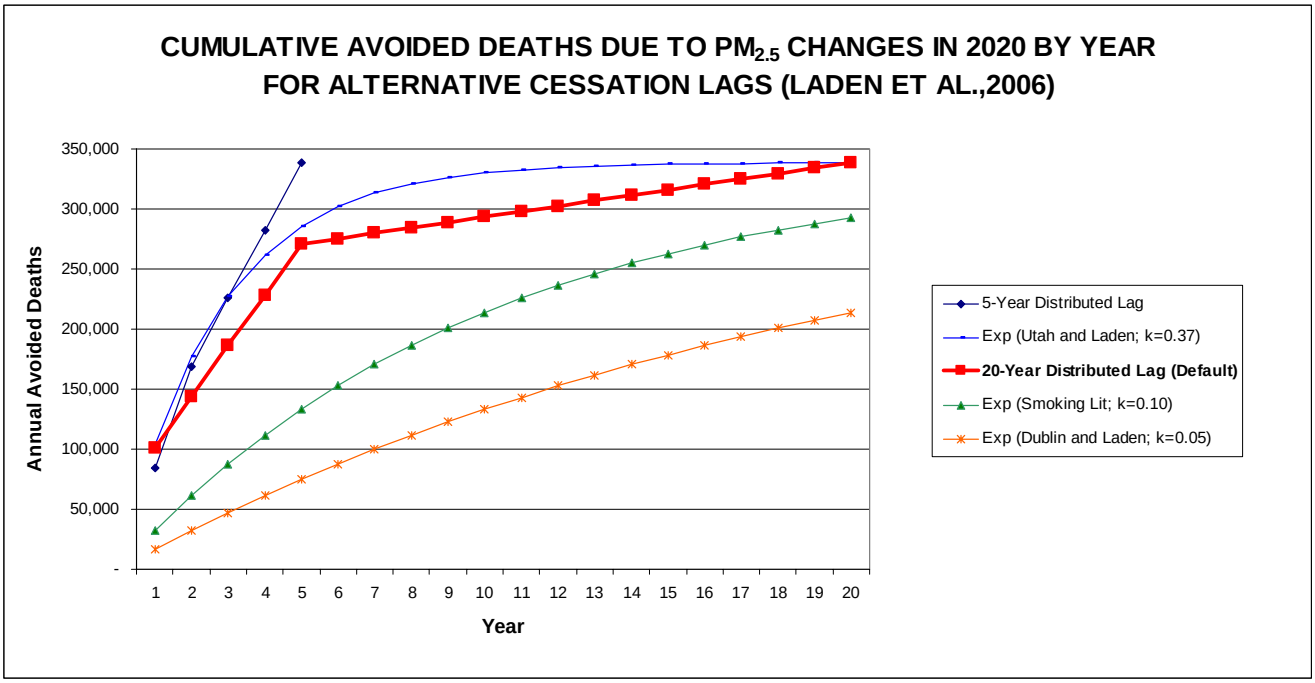


EXHIBIT 6-8 MEAN VALUATION RESULTS USING ALTERNATIVE LAG STRUCTURES - LADEN ET AL., 2006

MORTALITY CESSATION LAG	MEAN VALUATION (MILLION 2006$)		
	2000	2010	2020
20 Year Distributed Lag (Default)	**$1,100,000**	**$1,800,000**	**$2,600,000**
5 Year Distributed Lag	$1,200,000	$1,900,000	$2,800,000
Smooth Function, k = 0.05	$720,000	$1,100,000	$1,700,000
Smooth Function, k = 0.10	$930,000	$1,500,000	$2,200,000
Smooth Function, k = 0.37	$1,200,000	$1,900,000	$2,800,000
No Lag, No Discounting	$1,300,000	$2,000,000	$3,000,000

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.[1]

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.[2] 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 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

[1] 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.

[2] 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 PM2.5 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.

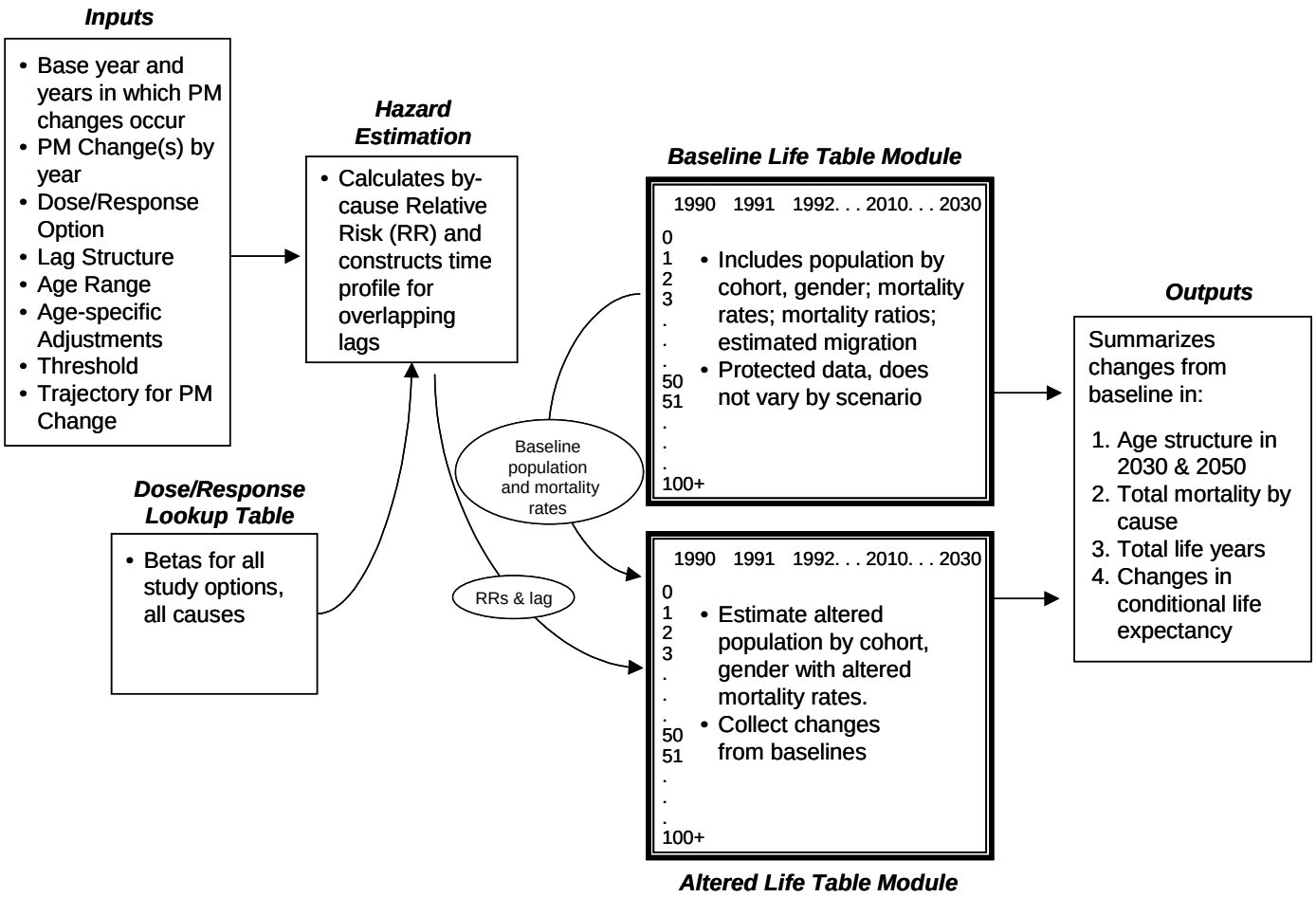
The model consists of five linked components, as illustrated in Exhibit 7-1: Inputs, Hazard Estimation, Baseline Life Table, Regulatory Life Table, and Outputs. The five components include seven spreadsheets in total, one each for Inputs, Hazard Estimation, and Outputs, and two each (one for males and 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.[3]

[3] 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 Pope et al. (2002) 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 7-2. 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	0	0	1	1	1	1	1	1	1	1
5 to 9	0	0	0	0	0	0	0	0	0	0	0	0
10 to 14	0	0	0	0	0	0	0	0	0	0	0	0
15 to 19	0	0	0	0	0	0	0	0	0	0	0	1
20 to 24	0	0	0	0	0	0	0	0	0	0	0	1
25 to 29	0	0	0	0	0	0	0	0	0	0	0	0
30 to 34	0	(313)	(515)	(716)	(866)	(1,061)	(1,208)	(1,206)	(1,099)	(1,115)	(1,100)	(1,079)
35 to 39	0	(414)	(812)	(1,022)	(1,159)	(1,314)	(1,521)	(1,566)	(1,515)	(1,382)	(1,385)	(1,365)
40 to 44	0	(496)	(1,202)	(1,480)	(1,578)	(1,700)	(1,841)	(1,963)	(1,962)	(1,889)	(1,711)	(1,714)
45 to 49	0	(582)	(1,579)	(2,147)	(2,503)	(2,541)	(2,629)	(2,636)	(2,733)	(2,709)	(2,601)	(2,346)
50 to 54	0	(685)	(1,986)	(2,923)	(3,740)	(4,168)	(4,084)	(3,926)	(3,816)	(3,937)	(3,883)	(3,720)
55 to 59	0	(852)	(2,346)	(3,924)	(5,075)	(6,223)	(6,703)	(6,095)	(5,683)	(5,507)	(5,655)	(5,574)
60 to 64	0	(1,215)	(2,903)	(4,565)	(6,664)	(8,247)	(9,755)	(9,729)	(8,596)	(8,002)	(7,724)	(7,955)
65 to 69	0	(1,766)	(3,836)	(5,353)	(7,289)	(10,297)	(12,402)	(13,687)	(13,380)	(11,957)	(11,199)	(11,006)
70 to 74	0	(2,351)	(5,271)	(6,437)	(7,643)	(9,965)	(13,553)	(15,034)	(16,115)	(15,774)	(14,133)	(13,321)
75 to 79	0	(2,612)	(6,459)	(7,762)	(8,152)	(9,320)	(11,789)	(14,756)	(15,856)	(17,068)	(16,820)	(15,308)
80 to 84	0	(2,659)	(6,217)	(7,438)	(7,673)	(7,691)	(8,514)	(9,693)	(11,664)	(12,621)	(13,799)	(14,004)
85 to 89	0	(2,119)	(4,615)	(4,268)	(4,239)	(3,809)	(3,435)	(2,873)	(2,654)	(3,078)	(3,480)	(4,366)
90 to 94	0	(1,150)	(1,743)	(504)	765	2,145	3,241	4,495	5,775	7,493	9,602	10,269
95 to 99	0	(310)	90	1,165	3,013	5,009	7,317	9,299	10,449	12,157	15,368	19,951
100+	0	(49)	187	736	1,810	3,480	5,586	8,524	11,092	13,142	15,702	19,775
Total Change in Deaths:	0	(17,572)	(39,207)	(46,638)	(50,991)	(55,701)	(61,289)	(60,843)	(57,754)	(52,244)	(42,814)	(31,759)

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	5	74	209	537	636	788	992	1,180	1,308	1,436	1,588
5 to 9	0	0	5	73	208	535	635	786	990	1,178	1,306	1,434
10 to 14	0	0	0	5	73	208	535	634	786	990	1,178	1,305
15 to 19	0	0	0	0	5	73	208	534	633	785	989	1,177
20 to 24	0	0	0	0	0	5	73	207	532	631	783	986
25 to 29	0	0	0	0	0	0	5	73	207	531	629	780
30 to 34	0	296	759	1,248	1,494	1,920	2,165	2,382	2,228	2,360	2,660	2,722
35 to 39	0	570	2,646	4,358	5,677	6,694	8,141	8,961	9,070	8,303	8,478	8,672
40 to 44	0	677	3,847	8,496	10,458	12,437	14,209	16,576	17,445	17,302	15,756	15,910
45 to 49	0	790	4,882	12,362	17,724	20,100	22,562	24,817	27,701	28,468	27,921	25,329
50 to 54	0	922	6,044	15,898	25,954	33,290	35,630	38,125	40,110	43,523	44,044	42,891
55 to 59	0	1,158	7,206	19,890	34,485	49,336	58,902	60,004	61,054	62,295	66,361	66,443
60 to 64	0	1,673	9,026	23,272	44,389	65,605	86,788	98,033	94,901	93,431	93,505	98,375
65 to 69	0	2,520	12,594	28,164	51,534	85,163	115,387	144,165	154,480	144,940	140,056	138,629
70 to 74	0	3,415	17,959	37,078	59,415	93,375	143,030	182,851	217,232	225,959	208,803	199,834
75 to 79	0	3,917	23,165	50,202	72,951	101,435	147,254	213,903	259,913	299,829	306,957	281,588
80 to 84	0	4,218	24,680	60,155	90,034	114,201	147,784	203,774	282,960	334,227	380,073	386,629
85 to 89	0	3,739	22,972	55,562	92,439	122,370	145,677	180,759	239,503	325,735	380,787	431,916
90 to 94	0	2,481	15,562	39,545	67,388	101,559	127,916	147,669	178,136	233,069	316,690	371,797
95 to 99	0	1,041	6,642	17,256	34,015	53,805	78,844	97,987	111,475	134,960	178,484	246,571
100+	0	311	1,788	4,950	11,669	22,832	38,384	59,753	80,526	100,320	127,277	171,954
Total Life Years Gained	0	27,734	159,852	378,724	620,451	885,580	1,174,917	1,482,985	1,781,063	2,060,144	2,304,174	2,496,530

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 74.7 million additional life years lived in the US population.

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.[4] Effects on life expectancy are immediately experienced across all cohorts, and grow rapidly to a gain in the with-CAAA scenario of approximately one-half year 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 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.

[4] 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 7-4. 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	0.00	0.09	0.23	0.33	0.40	0.47	0.53	0.55	0.55	0.55	0.55	0.55
10	0.00	0.09	0.23	0.33	0.40	0.47	0.53	0.55	0.56	0.56	0.55	0.55
20	0.00	0.09	0.23	0.33	0.40	0.47	0.53	0.55	0.56	0.56	0.56	0.55
30	0.00	0.10	0.23	0.33	0.41	0.48	0.54	0.56	0.56	0.56	0.56	0.55
40	0.00	0.09	0.22	0.32	0.39	0.46	0.51	0.54	0.54	0.54	0.54	0.53
50	0.00	0.08	0.21	0.30	0.37	0.43	0.49	0.51	0.51	0.52	0.51	0.51
60	0.00	0.07	0.18	0.27	0.33	0.39	0.44	0.46	0.47	0.47	0.47	0.47
70	0.00	0.06	0.15	0.22	0.27	0.32	0.36	0.38	0.39	0.39	0.39	0.39
80	0.00	0.04	0.11	0.16	0.20	0.24	0.27	0.28	0.29	0.29	0.29	0.29
90	0.00	0.03	0.07	0.10	0.12	0.14	0.15	0.16	0.16	0.16	0.16	0.16
100+	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

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 two – in 2020, for example, the dynamic approach estimates almost 4 million life years saved through 2050, while the BenMAP approach estimates just more than 2 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	45,234	59,717	5,267	5,435
35	44	143,633	161,788	51,332	57,714
45	54	248,562	262,899	139,270	146,227
55	64	353,304	478,477	326,448	329,696
65	74	328,485	553,108	660,371	711,835
75	84	297,882	376,579	1,012,853	1,192,017
85	99	134,954	185,015	1,284,263	1,539,837
	Total	1,552,054	2,077,583	3,479,803	3,982,762