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User's Manual for the Co-Benefits Risk Assessment (COBRA) Screening Model

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**Developed for
Climate Protection Partnerships Division
State and Local Climate and Energy Programs**



State Climate and Energy Program

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INSTALLATION INSTRUCTIONS

System Requirements

Users must have at least 2 GB free hard drive space, 1 GB of RAM, and a CD-ROM drive. COBRA was designed and tested on Windows XP. There are no known issues with regards to running COBRA on Windows Vista or Windows 7.

Installation

COBRA can be downloaded directly to your computer or installed from a CD sent to you in the mail. If you are downloading the COBRA model, note that the installer file is large and the amount of time required to complete the download will depend on your connection speed. Find the program 'setup.exe' in the location where the installer file was saved. If you are installing the COBRA model from a CD, exit all programs and insert the Installation disk into your CD-ROM drive. The installation program may start automatically; if not, go to **Start... Run...** and then find the program 'setup.exe' in your computer's CD-ROM drive.

During installation, follow the prompts on your screen. COBRA is a large program, and depending on the speed of your computer, it may take five minutes to an hour to complete the installation.

Launching the Model

To launch the model, go to **Start... Programs... COBRA**. To allow COBRA to run efficiently, turn off any antivirus programs.

Technical Assistance

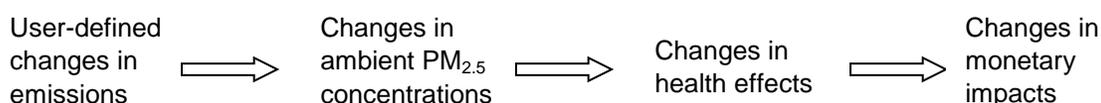
For more information, please contact Denise Mulholland at 202-343-9274 or mulholland.denise@epa.gov.

CHAPTER 1.

Introduction

What is COBRA?

COBRA is a screening tool that provides preliminary estimates of the impact of air pollution emission changes on ambient particulate matter (PM) air pollution concentrations, translates this into health effect impacts, and then monetizes these impacts,¹ as illustrated below.



The model does not require expertise in air quality modeling, health effects assessment, or economic valuation. Built into COBRA are emissions inventories, a simplified air quality model, health impact equations, and economic valuations ready for use, based on assumptions that EPA currently uses as reasonable best estimates. Analyses can be performed at the state or county level and across the 14 major emissions categories (these categories are called “tiers”) included in the National Emissions Inventory.^{2,3}

COBRA presents results in tabular as well as geographic form, and enables policy analysts to obtain a first-order approximation of the benefits of different mitigation scenarios under consideration and to quickly compare outcomes in terms of PM_{2.5} air quality or health effects. However, *COBRA is only a screening tool*. More sophisticated, albeit time-consuming, modeling approaches are currently available to obtain a more refined picture of the health and economic impacts of changes in emissions.

¹ In calculating health impacts, COBRA generates mean estimates of health impacts. This is in contrast to a risk assessment, which typically builds in a margin of safety by presenting 95th percentile estimates.

² The emissions inventory in COBRA includes fourteen broad tier 1 categories (e.g., on-road motor vehicles); within each of these larger categories there are tier 2 (e.g., diesels), and tier 3 (e.g., heavy duty diesels) categories. The fourteen tier 1 categories include: Chemical & Allied Product Manufacturing, Fuel Comb Electric Utilities, Fuel Combustion Industrial, Fuel Combustion Other, Highway Vehicles, Metals Processing, Miscellaneous, Natural Sources, Off-Highway, Other Industrial Processes, Petroleum & Related Industries, Solvent Utilization, Storage & Transport, and Waste Disposal & Recycling.

³ Details on emissions categories are available at: <http://www.epa.gov/ttnchie1/net/2008inventory.html>

How is COBRA used?

COBRA can be used to quickly identify important emission sources and compare the impacts of different types of control options. Using the mapping capabilities in COBRA, users can identify the locations and types of emissions sources that contribute to local air quality problems. When considering different policy options, COBRA can help identify those options that are likely to maximize health benefits, or that could be expected to achieve health risk reductions in the most cost-effective manner. Once state and local officials narrow the set of most promising policy options through COBRA, they can then conduct analyses with more sophisticated air quality models to finalize their policy choices.

The model contains detailed emissions estimates for the year 2017, developed for the Mercury and Air Toxics Standards (MATS) Final Rule (77 FR 9304-9513), which limits mercury and other toxic air pollution from coal- and oil-fired power plants.⁴ The assumptions underlying these emissions data are detailed in the Emissions Modeling for the Final MATS Technical Support Document (U.S. EPA, 2011b). The air quality modeling platform for MATS is based on emissions data, meteorology, initial conditions, and boundary conditions from 2005 and uses 2017 as the future year of analysis. COBRA uses the 2017 “control case” developed by EPA for the MATS Rule, which includes:

- electrical generating unit emissions (reflecting the implementation of both MATS and the Cross-State Air Pollution Rule),⁵
- mobile emissions (reflecting the impacts of implementation of the Energy Independence and Security Act of 2007 and the Energy Policy Act of 2005 on mobile source fuels), and
- average year fire data.

Who can use COBRA?

- **State and local officials** who would like to quickly identify important emission sources and compare the impacts of different control options;
- **Analysts** looking to improve their understanding of the air quality improvements and health benefits associated with clean energy policies under consideration;
- **Environmental agencies** trying to inexpensively screen through many options to identify those that maximize the health benefits and to quantify the economic value of health improvements;
- **Energy officials** looking to estimate and promote the air quality, health, and associated economic co-benefits of their energy efficiency or renewable energy policies; and
- **Transportation planners** interested in understanding the air quality and health impacts of fuel switching or reductions in vehicle miles traveled.

⁴ Read about the current status of MATS at <http://www.epa.gov/airquality/powerplanttoxics/actions.html>.

⁵ On August 21, 2012, the U.S. Court of Appeals for the D.C. Circuit issued an opinion that would vacate the Cross State Air Pollution Rule. On October 5, 2012 the United States filed a petition seeking rehearing of that decision. Further information about CSAPR (77 FR 34830) is available at: <http://www.epa.gov/airtransport/>.

COBRA users can create their own new scenarios by specifying increases or reductions to the emissions estimates for the analysis year (i.e., 2017). Emissions changes can be entered at the county, state, or national level.

COBRA then generates changes in $PM_{2.5}$ concentrations between the baseline scenario (the “business-as-usual” estimates for the analysis year) and the control scenario (the analysis year modified by the user’s emissions changes). A source-receptor matrix translates the air pollution emissions changes into changes in ambient $PM_{2.5}$ (for more information about the emissions inventory and the source-receptor matrix, see Appendix A). Using a range of health impact functions, COBRA then translates the ambient $PM_{2.5}$ changes into changes in the incidence of human health effects (see Appendices B through E). Finally, the model places a dollar value on these health effects (for more information, see Appendix F).⁶ COBRA estimates the change in air pollution-related health impacts, and estimates the economic value of these impacts, using an approach that is generally consistent with EPA Regulatory Impact Analyses (U.S. EPA, 2012f; U.S. EPA, 2012g). These analyses reflect the current state of the science regarding the relationship between particulate matter and adverse human health.

Outcomes can be modeled nationwide or for smaller geographic areas. Results include changes in ambient $PM_{2.5}$ concentrations, and changes in the number of cases of a variety of health endpoints that have been associated with $PM_{2.5}$. These health endpoints include:

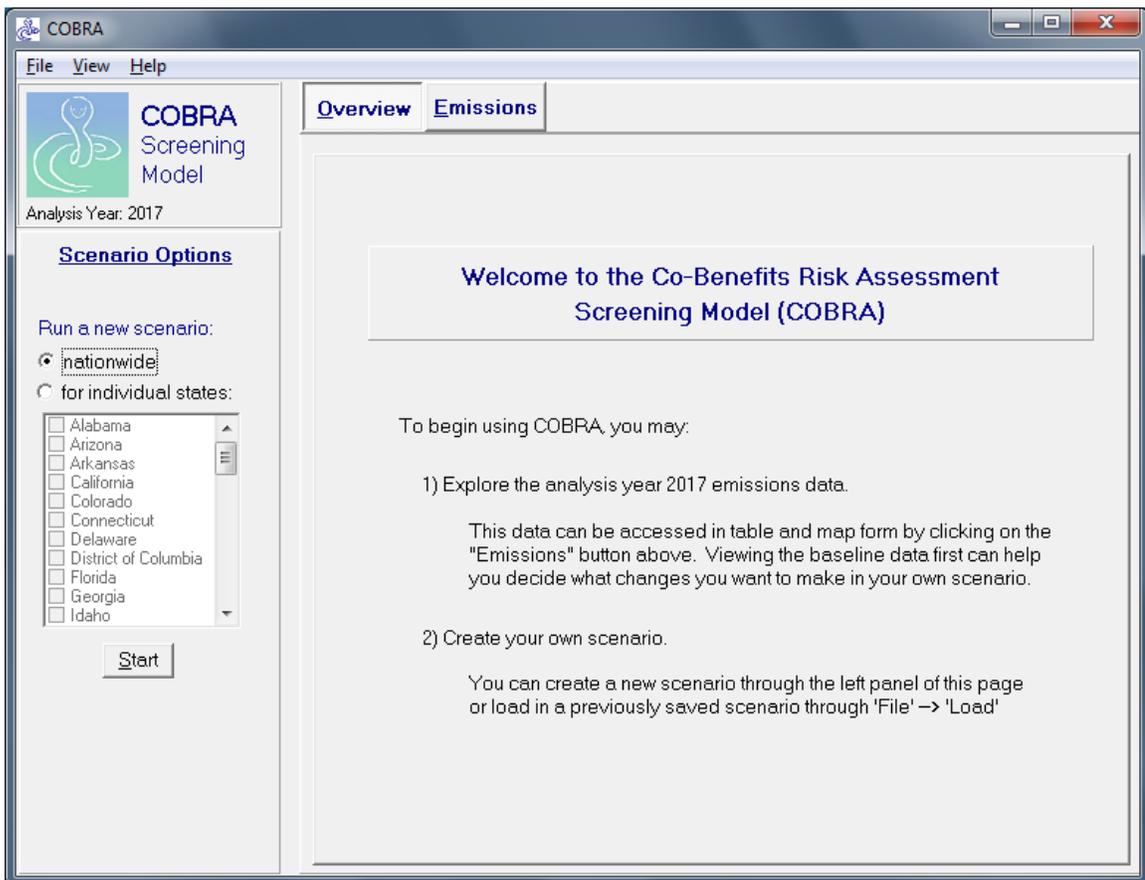
- Adult and infant mortality;
- Non-fatal heart attacks;
- Respiratory-related and cardiovascular-related hospitalizations;
- Acute bronchitis;
- Upper and lower respiratory symptoms;
- Asthma-related emergency room visits;
- Asthma exacerbations;
- Minor restricted activity days (i.e., days on which activity is reduced, but not severely restricted); and
- Work days lost due to illness.

⁶ There is a large literature regarding the health impacts of air pollution and approaches to value these impacts. COBRA uses a subset that EPA deems most credible. More sophisticated users interested in using additional approaches may want to use EPA’s Environmental Benefits Mapping and Analysis Program (BenMAP), which is available at: <http://www.epa.gov/air/benmap/>.

Users can view the results in tabular or map form as well as export the data for use in their own communications.

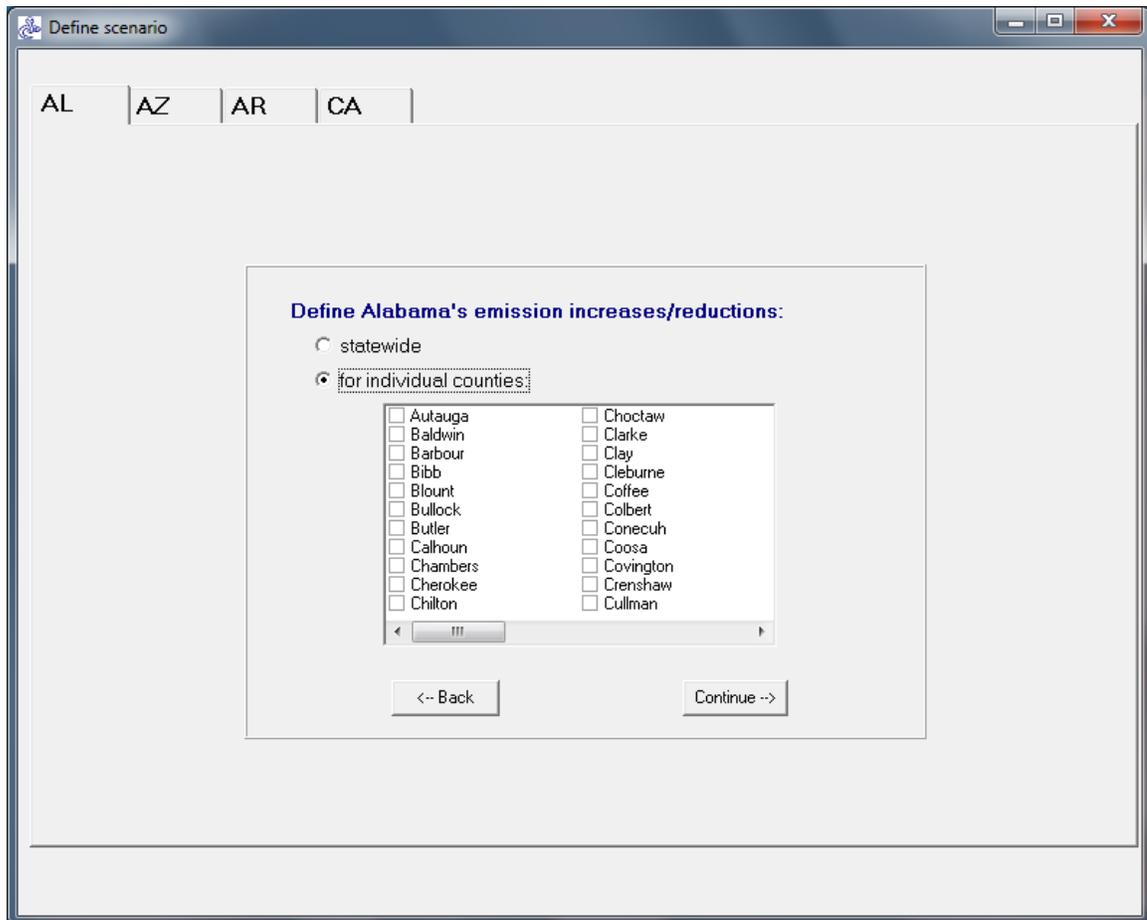
Overview of Model

The COBRA screening model is a stand-alone Windows application that contains all of the data needed for the analysis of alternative emissions scenarios; the user is only required to enter changes in emissions. Upon launching the model, you will see the **Overview** screen, which explains that you may do one of two things: explore the baseline emissions data, or create your own emissions scenario. Even if you are mainly interested in creating your own scenario, you may want to look at the baseline data first, since new scenarios are created by specifying increases or decreases to the baseline for one or more tier categories.



Once you are ready to run a comparison, return to the **Overview** screen and use the Scenario Options panel on the left of the screen to indicate the geographic level at which you wish to make your emissions changes. ‘Nationwide’ means that any emissions changes will be applied to all sources in that category throughout the entire U.S.

Alternatively, you can select ‘for individual states’ and select one or more states in the window below. Any emissions changes you make will be applied only to those selected states. On the following screens you can indicate if you want to make changes at the county level of individual states; if so, you can combine some or all of the counties into groups. Note that COBRA allows you to enter individual county changes for up to 10 counties per state.



Once your geography is determined, you can enter your emissions changes for the nation, or for each state, county, or group of counties, depending on your previous selection. COBRA provides three levels of emissions sources (tiers) in a directory tree structure.

The choice of the category depends on the source that a policy or action is expected to affect. For example, to assess the impacts of a renewable energy or energy efficiency policy that is expected to affect utility-related emissions, you would select ‘FUEL COMB. ELEC. UTIL.’ as the first tier. If you know the specific fuel source within the utility category that would be reduced or displaced (e.g. coal or natural gas), you can select the appropriate second tier. For a policy that involves fuel switching or reductions

in transportation through vehicle miles travelled, you would select ‘HIGHWAY VEHICLES’ as the first tier.

Exhibit 1. Basic Tools and Data Sources for Determining Emission Reductions

Online Tool	Description
EPA’s Emissions & Generation Resource Integrated Database (eGrid) (http://www.epa.gov/cleanenergy/energy-resources/egrid/index.html)	Provides data on the environmental characteristics of electric generation by power plants in the United States.
EPA’s AVOIDed Emissions and geneRation Tool (AVERT) (http://epa.gov/avert/)	Estimates displaced emissions (at the county, state, and regional levels) at electric power plants due to renewable energy or energy efficiency policies and programs.
eCalc (http://ecalc.tamu.edu/)	Uses both energy and emissions modeling to determine emission reductions from energy efficiency and renewable energy programs in the Electric Reliability Council of Texas region.
EPA’s Motor Vehicle Emission Simulator (MOVES) (http://www.epa.gov/otaq/models/moves/index.htm)	Estimates emissions from mobile sources, including emissions from cars, trucks, and motorcycles.
National Emissions Inventory (http://www.epa.gov/ttnchie1/net/2008inventory.html)	Allows users to view emissions by sector (for 60 emissions inventory sectors) for specific pollutants at varying levels of geographic aggregation.
OTC Workbook (http://www.otcair.org)	Predicts emission reductions from energy portfolio policies and energy efficiency programs and other measures affecting renewable resources or multiple pollutants.
Power Profiler (www.epa.gov/powerprofiler/)	Allows users to view the emissions that can be attributed to electricity use in homes or businesses.

Note: For more details on these basic tools and on other methods, see: (1) Chapter 4 of EPA’s “Assessing the Multiple Benefits of Clean Energy: A Resource for States” report (U.S. EPA, 2011a), available at <http://www.epa.gov/statelocalclimate/resources/benefits.html>; or (2) Appendix I of EPA’s “Roadmap for Incorporating Energy Efficiency/Renewable Energy Policies and Programs into State and Tribal Implementation Plans” (U.S. EPA, 2012e), available at <http://www.epa.gov/airquality/eere/pdfs/appendixI.pdf>.

Once you have determined the appropriate tier category, click on it and enter the emission changes in tons or percentages, for one or more of the six included pollutants. Absolute emission reductions in tons can be estimated using a variety of methods ranging from basic to sophisticated. See Exhibit 1 above for a description of a few basic methods. Percentage reductions can be used to assess the benefits of a goal that calls for reductions in activity levels or emissions from a particular source, such as a renewable portfolio

standard, transportation policies requiring reductions in vehicle miles traveled, and energy efficiency programs.

For example, EPA's Emissions & Generation Resource Integrated Database (eGrid) website provides electric generation data and corresponding emissions rates for the United States. On the eGrid website, click on '**eGRID2012 year 2009 Summary Tables (PDF)**.' Using the Western Electricity Coordinating Council (WECC) Southwest Region (which includes Arizona and New Mexico) as an example, you can obtain the following information:

- Emissions: The "Year 2009 eGRID Subregion Emissions - Criteria Pollutants" table on page 2 summarizes emissions data in several regions. The annual sulfur dioxide (SO₂) emissions for the WECC Southwest Region in 2009 were approximately 58,000 tons.
- Electric Generation: The "Year 2009 eGRID Subregion Resource Mix" table on page 5 summarizes electric generation data by region. The net generation for the WECC Southwest Region in 2009 was approximately 186 million megawatt hours (MWh).
- Emissions Rates: The "Year 2009 eGRID Subregion Output Emission Rates - Criteria Pollutants" table on page 4 provides the WECC Southwest Region's non-baseload output emissions rate for SO₂: 0.3913 lbs. per MWh.⁷

If a policy is expected to reduce electric generation by 20% in the WECC Southwest Region, we can calculate the reduction in MWh: $20\% \times 186 \text{ million MWh} = 37 \text{ million MWh}$. We can then calculate the emission reductions as:

$$\text{Emission Reduction} = 37 \text{ million MWh} \times 0.3913 \text{ per MWh} = 14 \text{ million lbs.}$$

This reduction is equal to 7,000 tons (14 million lbs. \div 2000 lbs. per ton) of SO₂.

After you have calculated emissions changes, you can enter these changes for as many tier categories as you wish, and different sets of changes for each state, county, or county group.

⁷ Non-baseload emissions come from power plants that are brought online only when there is excess demand (U.S. EPA, 2012b).

With your emissions changes entered, click **Apply Edits** to ensure that the changes are effective, then **Run Scenario** to run the comparison between the scenario you have just created and the baseline scenario. The model will ask you to choose a discount rate (more detail (described in more detail in the Chapter 2 Tutorial) and name the scenario before it starts. When the model is done running, you can examine the results.

Regardless of the geographic level at which you made your emissions changes, you can examine the results for every county in every state in the country. For each county, COBRA calculates three types of results: the change in ambient $PM_{2.5}$ concentration; the change in health effects associated with that change; and the dollar value associated with the change in health effects.

These results can be viewed in tables in the results section, or graphically on a map of the U.S. You can select the specific states or effects of interest in the tables from the dropdown tab under “View New Table By...” For the map, you can zoom and drag the map to get to the scale of interest and then select the results you want to see.

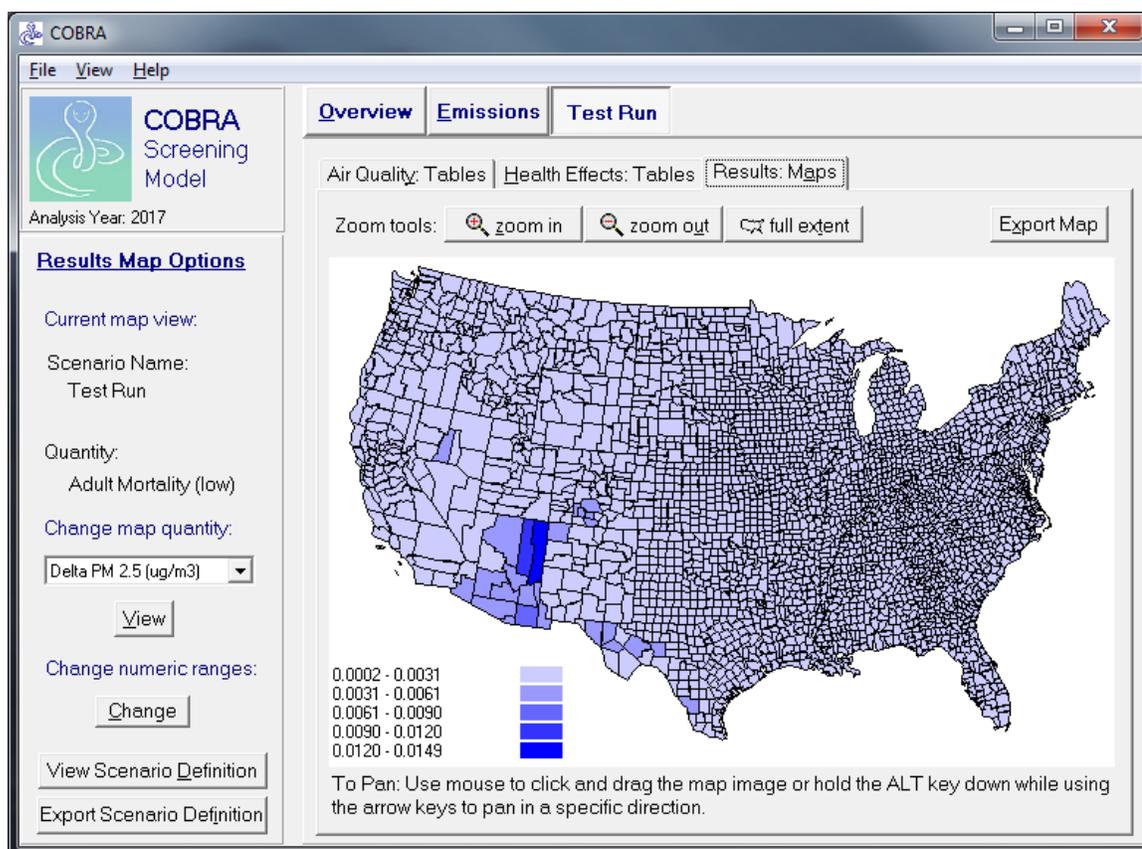
The screenshot shows the COBRA Screening Model interface. The window title is "COBRA". The menu bar includes "File", "View", and "Help". The main interface has three tabs: "Overview", "Emissions", and "Test Run". Under the "Test Run" tab, there are sub-tabs for "Air Quality: Tables", "Health Effects: Tables", and "Results: Maps".

On the left side, there is a sidebar with the COBRA logo and "Screening Model" text. Below this, it says "Analysis Year: 2017". There are links for "Air Quality Table Options" and "Table Options". Under "Current table:", it shows "Scenario Name: Test Run". Under "View:", it shows "All States". There is a "View new table by:" section with a dropdown menu set to "--choose state--" and a "View" button. At the bottom of the sidebar are buttons for "View Scenario Definition" and "Export Scenario Definition".

The main area displays a table with the following columns: FIPS, County, State, Control PM 2.5, Base PM 2.5, and Delta PM 2.5. The table contains 15 rows of data for various counties in Indiana. An "Export current data view" button is located above the table.

FIPS	County	State	Control PM 2.5	Base PM 2.5	Delta PM 2.5
18151	Steuben	IN	10.208	10.209	.001
18153	Sullivan	IN	10.329	10.33	.0012
18155	Switzerland	IN	10.286	10.287	.0009
18157	Tippecanoe	IN	10.885	10.886	.0011
18159	Tipton	IN	11.148	11.149	.0009
18161	Union	IN	10.514	10.515	.0009
18163	Vanderburgh	IN	10.859	10.86	.0009
18165	Vermillion	IN	10.736	10.738	.0012
18167	Vigo	IN	10.632	10.633	.0012
18169	Wabash	IN	11.087	11.088	.001
18171	Warren	IN	10.856	10.857	.0012
18173	Warrick	IN	9.143	9.144	.0009
18175	Washington	IN	9.943	9.944	.0009
18177	Wayne	IN	10.606	10.607	.0009

Below the table, there is a note: "Data estimates for 2017. All values are in ug/m3. To sort by column, click on the column title. To filter the data view, use the arrows on the state/county columns. A positive value indicates a decrease from the base scenario."



Results sets and subsets, including maps, can be exported for use in outside programs and presentations. Scenario results can be saved and reloaded into COBRA at a future time. To save your results, click on **File... Save** and then select your scenario from the list of currently open scenarios. To reload results that you have previously saved, click on **File... Load** and then browse to the location on your computer where the results are saved. Up to five sets of results can be loaded at once; you can toggle back and forth between them. At any time in the program you can view your scenario definition (the summary of emissions changes you have made to the baseline), or export it for future reference by clicking on **Export Scenario Definition**.

Caveats and Limitations

There are limitations to the COBRA screening model that make it inappropriate for certain types of analyses:

- *Complicated analyses.* Scenarios involving hundreds or perhaps thousands of different changes in emissions from sources over a wide geographic area, for example, would take a prohibitive amount of time, due to limitations in the user interface.

- *Determination of attainment.* Modeling the attainment of national ambient air quality standards requires more sophisticated air quality modeling than that currently built into COBRA.
- *Estimating rebound effects.* Emissions in some states and regions are “capped” and emission allowances are traded across entities within the designated area. In these areas, a reduction in emissions in one location may result in an increase (rebound) in emissions in another area under the cap, unless the emission allowances are retired through the scenario evaluated. COBRA does not automatically capture this potential effect so care should be exercised when using COBRA to analyze the net impacts of a change in policy. COBRA is more suited to an attributable risk assessment, which addresses the magnitude of an emission source and the impact of controlling its emissions. That information can be used to develop policies targeted to the appropriate sources.

Because COBRA is intended primarily as a screening tool, it uses a relatively simple air quality model, which introduces additional uncertainty. While some comparative work to test the performance of COBRA’s air quality model is ongoing, it is not yet fully validated.

As with more complex air pollution benefits models, there is substantial uncertainty surrounding the values of key inputs to COBRA – in the air quality model, emissions inventory, health impact functions, and economic values – and users should exercise caution when interpreting the results of analyses.

Some of the uncertainty in COBRA reflects variability (for example, a health impact function that is appropriate for one location may not be appropriate for another location if the function actually varies across locations). Much of the uncertainty, however, reflects the insufficient level of knowledge about the true values of model inputs.

The appendices discuss these issues and provide sources for additional information. However, developing a quantified confidence interval for the results is beyond the scope of this model. As an alternative, users should consider using sensitivity analyses to determine how their conclusions might change with differences in the location and amount of emissions. When more detailed analyses are required, users should be cognizant of the model’s limitations, and consider using more sophisticated modeling approaches.

Chapter 2 of this User’s Manual provides a quick tutorial for the new user. Baseline data are examined, and a simple new scenario is defined and run, and the results are displayed in tables and maps. The following chapters provide more detailed information on each step, and describe additional options you can use for more complicated analyses.

Chapter 3 describes the baseline emissions data you can examine using the Emissions button at the top of the Overview screen.

Chapter 4 provides details on different ways to define your new scenario, and run the comparison between it (the control scenario) and the baseline scenario.

Chapter 5 describes the different ways to view, export, and save your results, and to reload previously saved results.

A **Glossary** is provided at the end of the manual.

Additional Information

The Appendices to this manual provide additional information on the methods and assumptions used in the model.

- **Appendix A: Description of Source-Receptor Matrix and Emissions Data.** Describes the source-receptor matrix embedded within the model that translates the air pollution emissions changes into changes in ambient particulate matter.
- **Appendix B: Derivation of Health Impact Functions.** Explains the derivation of the types of health impact functions used in COBRA.
- **Appendix C: COBRA Health Impact Functions.** Provides an overview of all the health impact functions used in COBRA to convert changes in ambient PM_{2.5} into health effects.
- **Appendix D: Baseline Incidence Rates for Adverse Health Effects.** Lists the baseline incidence rates for each of the types of adverse health effects.
- **Appendix E: Population Forecasts.** Describes the population forecasting procedure.
- **Appendix F: Economic Value of Health Effects.** Lists the equations and sources of the values used to monetize the health effects.
- **Appendix G: Additional Quick Start Tutorials** on Sample COBRA Scenarios
- **Appendix H: References.** Provides all of the sources referenced in the Appendices or used in the model.

CHAPTER 2.

Quick-Start Tutorial

This tutorial will give you a quick introduction to how COBRA works, and how to work through the steps of a simple analysis. At each step, only the basic functions are described; for more advanced options, see the subsequent chapters.

COBRA allows you to estimate the impact of a change in air pollution resulting from a new policy or other type of change. In this example, we will consider changes in one state (we have arbitrarily selected Pennsylvania) that result in a decrease in emissions from electricity generating plants. If a statewide plan to switch 25 percent of electricity generation to renewable sources were put into effect, what would be the difference in ambient particulate matter levels and health effects, compared to doing nothing? This tutorial will show you how to use COBRA to examine this type of scenario through the following steps:

Step 1. Open the model.

Step 2. View the baseline emissions data.

Step 3. Select the geography for emissions changes.

Step 4. Define the emissions changes, select a discount rate, and run the comparison.

Step 5. View the results.

Step 6. Save or export your results.

Additional examples for assessing the impacts of a transportation policy, renewable energy supply standards, and energy efficiency programs can be found in Appendix G.

Step 1. Open the model.

To open COBRA, click **Start... All Programs... COBRA... COBRA**. The model will open. COBRA will load estimates of emissions, population, and other data for the analysis year (i.e., 2017) for you to view and modify. The results of your analysis will be expressed in terms of the difference between the baseline scenario (estimates for 2017 in absence of the policy) and the control scenario (estimates for 2017 reflecting effects of changes in emissions due to the policy). Note that the final results will be for 2017 only.

Step 2. View the baseline emissions data.

COBRA will display the main screen. You will see two tabs at the very top: **Overview** and **Emissions**. Click **Emissions** and you will see displayed all of the estimated emissions data for the country in 2017, by state, county, source category, and pollutant. To see emissions data for Pennsylvania only, change the selection in the drop down box under ‘View new table by’ from ‘All States’ to ‘Pennsylvania,’ and click **View**. Now you can scroll through the table to see the estimated emissions for 2017. In Step 4, you can choose to enter emissions as percentage changes; such emissions changes will be based on these estimates.

The screenshot shows the COBRA software interface. The window title is 'COBRA'. The menu bar includes 'File', 'View', and 'Help'. The main area has two tabs: 'Overview' and 'Emissions', with 'Emissions' selected. Below the tabs are two sub-tabs: 'Base Emissions: Tables' and 'Base Emissions: Maps'. A button labeled 'Export current data view' is located in the top right of the main area. The main area contains a table with the following data:

State	County	Tier1	Tier2
PA	Adams	FUEL COMB. INDUSTRIAL	COAL
PA	Adams	FUEL COMB. INDUSTRIAL	OIL
PA	Adams	FUEL COMB. INDUSTRIAL	GAS
PA	Adams	FUEL COMB. INDUSTRIAL	OTHER
PA	Adams	FUEL COMB. OTHER	COMMERCIAL/INSTITUTION
PA	Adams	FUEL COMB. OTHER	COMMERCIAL/INSTITUTION
PA	Adams	FUEL COMB. OTHER	COMMERCIAL/INSTITUTION
PA	Adams	FUEL COMB. OTHER	MISC. FUEL COMB. (EXCEPT
PA	Adams	FUEL COMB. OTHER	RESIDENTIAL WOOD
PA	Adams	FUEL COMB. OTHER	RESIDENTIAL WOOD
PA	Adams	FUEL COMB. OTHER	RESIDENTIAL OTHER
PA	Adams	FUEL COMB. OTHER	RESIDENTIAL OTHER
PA	Adams	FUEL COMB. OTHER	RESIDENTIAL OTHER
PA	Adams	OTHER INDUSTRIAL PROCESSES	AGRICULTURE, FOOD, & KIN

The sidebar on the left contains the 'COBRA Screening Model' logo and 'Analysis Year: 2017'. Below this is the 'Base Emissions Table Options' section, which includes 'Current table: Pennsylvania', 'Data for: Pennsylvania', and 'All Counties'. There are two dropdown menus for 'View new table by:' with 'Pennsylvania' and 'All Counties' selected. A 'View' button is located at the bottom of the sidebar.

Step 3. Select the geography for emissions changes.

Now that you have seen the baseline emissions, you can define the new (control) scenario to compare to the baseline scenario. The first step is to select the geographic area to which you want to apply the emissions changes. Note that once your comparison is run, you will be able to see results (changes in ambient PM_{2.5} levels and health effects) for the

entire country (although only a subset of states usually experience PM_{2.5} reductions and health benefits).

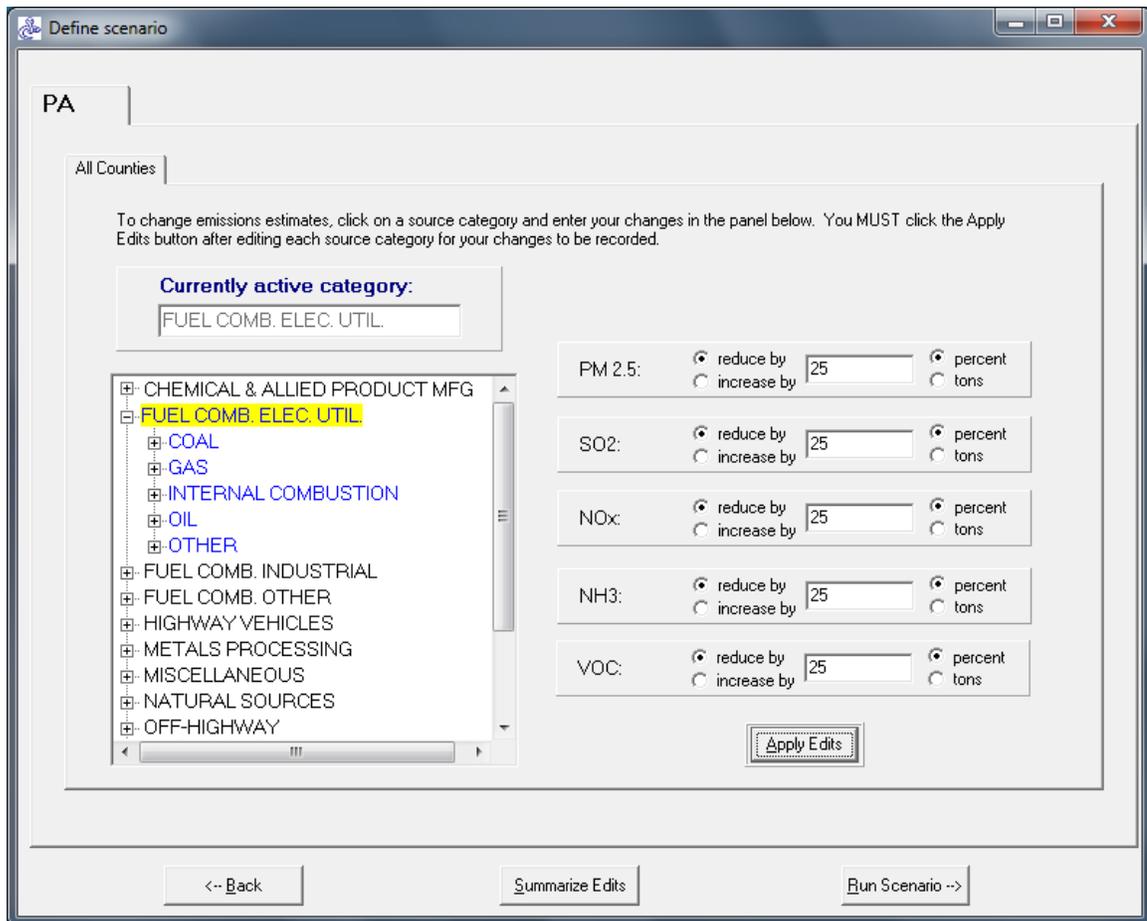
Click on the **Overview** tab. This is where you begin to define your scenario. In the left hand panel you can select your geography. Since we are only looking at changes statewide in Pennsylvania, click **'for individual states'** under 'Run a new scenario' and check the box next to 'Pennsylvania' in the list. Click **Start**.

COBRA will ask if you want define Pennsylvania's emission increases/reductions statewide or for individual counties. If you wanted to vary the emissions changes across counties, or only make changes in some counties, you would select the second option. For instance, if you know the counties in which sources that are likely to be affected (such as power plants) are located, you can enter emissions changes in those counties only. However, in this example we are looking at a statewide change, so select **'statewide'** and click **Continue**.

Step 4. Define the emissions changes, select a discount rate, and run the scenario.

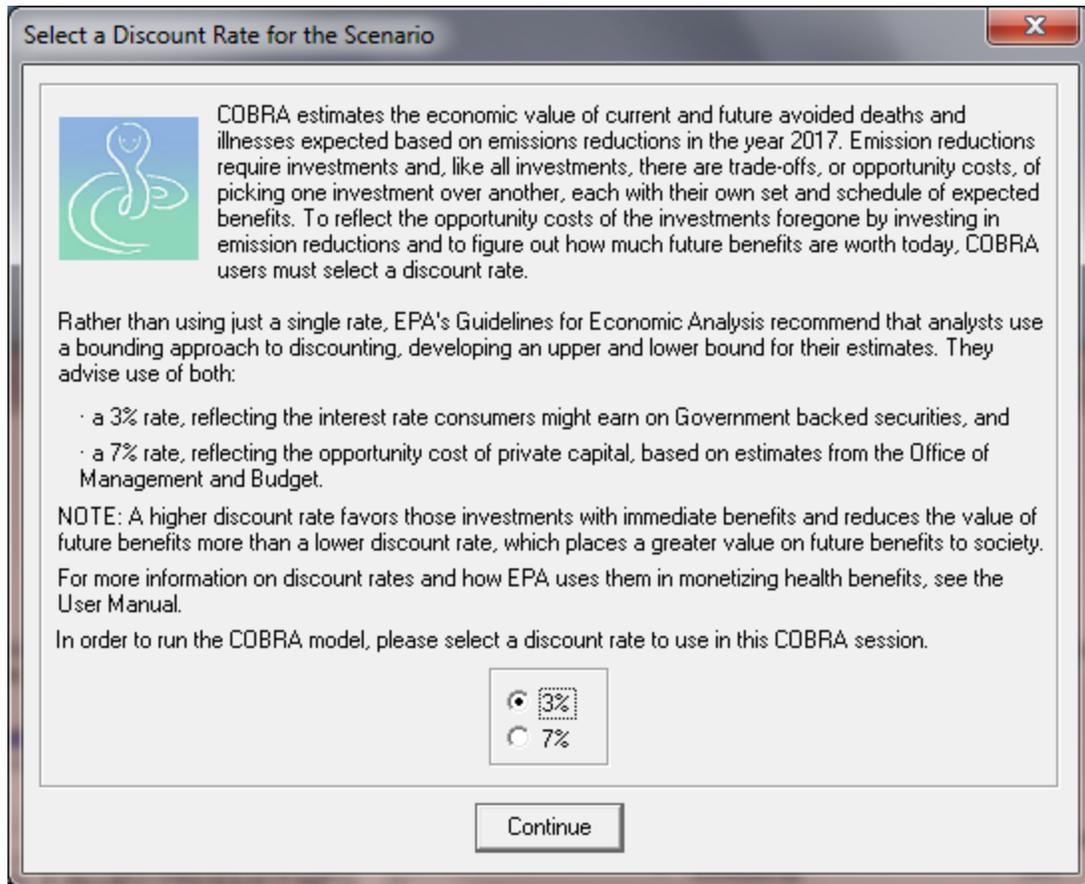
This page allows you to specify exactly how emissions will change in your control scenario. The bottom left window contains a directory tree with all of the tier 1, 2, and 3 source categories (see Appendix A for a list of source categories and their emissions). You can define emissions changes at any level, but each level always includes all the levels indented underneath it. In this example, we are only interested in electrical utilities, so click on the plus sign to the left of 'FUEL COMB. ELEC. UTIL.' This will open the tier 2 and 3 categories underneath. You can roll your mouse over any category and a yellow 'Tier Information' box will appear with the number of tons of each pollutant in the baseline emissions data for that source category, including all of the categories indented under it.

We want to change all of the source categories under 'FUEL COMB. ELEC. UTIL.', so click on that entry in the directory tree to highlight it. The boxes on the right-hand side of the screen list each pollutant included in the model. Since our scenario reduces all baseline emissions by 25 percent, type in '25' in the box next to each pollutant. The default selections are 'reduce by' and 'percent'; leave them as they are. Click **Apply Edits** to save your changes, COBRA will highlight the source categories that you have changed. Your screen should look like the one below. Click **Run Scenario**.

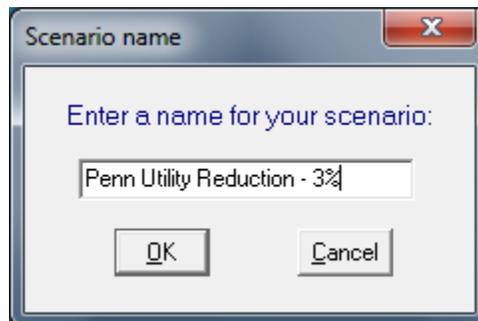


A pop-up box will open, asking you to choose a discount rate for the COBRA session. The discount rate you select is used to express future economic values in present terms. Not all health effects and associated economic values occur in the year of analysis (as explained in Step 5 below), and people are generally willing to pay more for something now than for the same thing later. Therefore, COBRA accounts for this time preference (i.e., a general preference for receiving benefits now rather than later) by discounting benefits received later. There is an ongoing discussion within the federal government about the most appropriate discount rate in this context; typically either 3% or 7% discount rates are used. Based on EPA's Guidelines for Preparing Economic Analyses (U.S. EPA, 2010a), it is recommended that COBRA users calculate monetized health benefits using both discount rates and then evaluate whether the overall outcome of the analysis is affected by the choice of discount rate. For more details on discount rates, see Appendix F.

In this scenario, we will use a 3% discount rate. Select 3% in the pop-up box and click **Continue**.



After selecting a discount rate, COBRA will ask you to supply a name for your scenario. You may want to include your choice of discount rate in the scenario name. Enter 'Penn Utility Reduction - 3%' (or whatever representative name you prefer) and click **OK**. You will see a message indicating that the scenario run is processing and may take a few minutes. The run time depends on your computer.

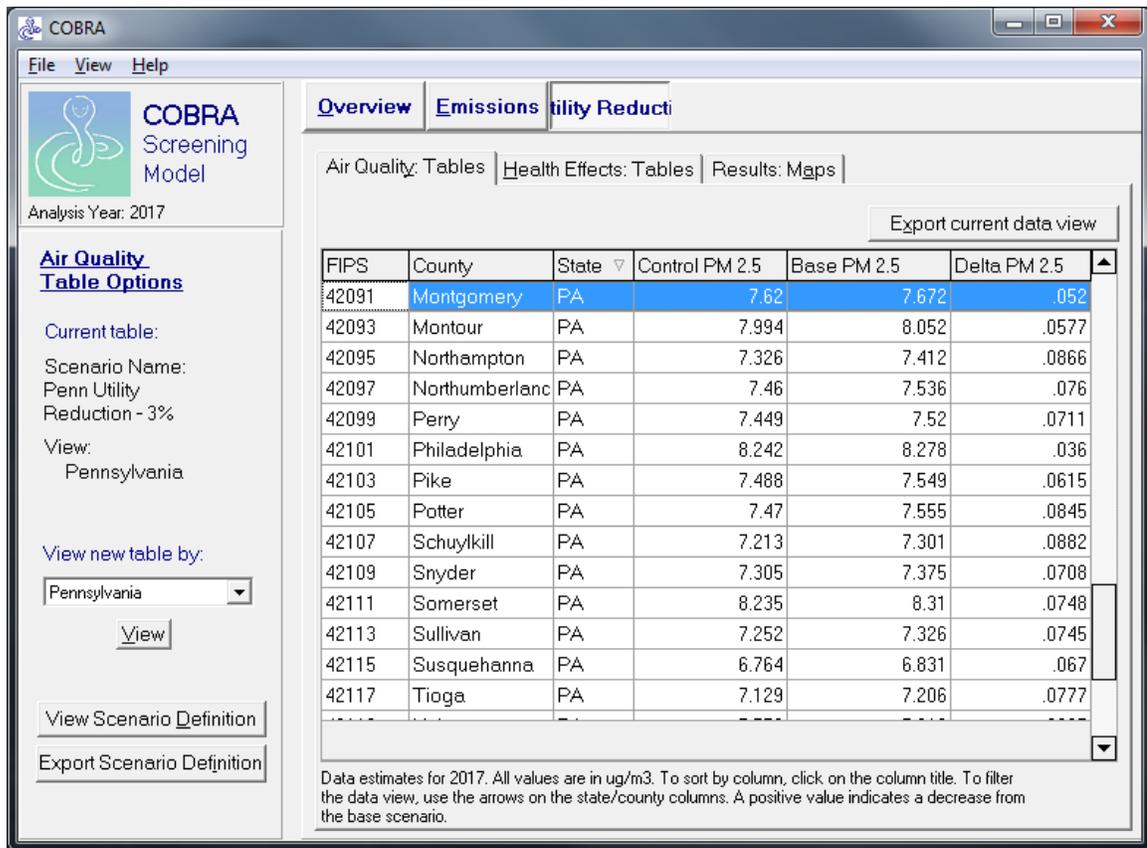


Step 5. View the results.

Once your run is complete, COBRA will display your results. You will see a screen with three tabs at the top: 'Air Quality: Tables,' 'Health Effects: Tables,' and 'Results: Maps.'

Click on the first tab, 'Air Quality: Tables.' This tab shows the change in air quality (PM_{2.5}) between the baseline scenario and your new scenario (the control scenario) for 2017. The default view shows the whole country, but since we expect the majority of the air quality changes to be in Pennsylvania, change the selection under 'View new table by' to Pennsylvania, and click **View**. The table will now display all the counties in Pennsylvania with the PM_{2.5} levels for your control scenario, the baseline scenario, and the change between them. Note that positive values indicate a reduction in PM_{2.5} in the control scenario.

Let's look at a specific county in Pennsylvania. Scroll down and find 'Montgomery County' in the table, or filter the county level by clicking on the arrow next to 'County' and selecting 'Montgomery' from the drop-down list. You will see that in Montgomery County, the estimated ambient PM_{2.5} concentration in the control scenario is 7.62 µg/m³, compared to the estimated baseline concentration of 7.672 µg/m³. The difference between the two estimated concentrations (Delta PM_{2.5}) is 0.052 µg/m³, which is the estimated change in air quality due to the 25% reduction in emissions from fuel combustion electricity generating plants in the whole state (the change in concentration is due to decreases in emissions from plants within the county plus plants in other counties). Note that positive changes indicate a lower concentration in the control scenario. If the Delta PM_{2.5} were negative, it would indicate an increase in concentration.



Now click on the ‘**Health Effects: Tables**’ tab. Select ‘Pennsylvania’ in the list and click **View**. This screen shows, for each county in Pennsylvania, the estimated change in health effects caused by the estimated change in ambient PM_{2.5} levels, as reported on the Air Quality tab. Each change in health effect also has an associated dollar value.

Scroll down in the list of counties (click on ‘**County**’ to sort alphabetically by county) or use the filter to display Montgomery County, which had a 0.052 µg/m³ reduction in ambient PM_{2.5}, as shown on the Air Quality tab. This table shows the reductions in health effects associated with that 0.052 µg/m³ decrease. Note that positive values indicate a decrease in impacts (that is, fewer cases of illness/premature mortality or avoided economic loss). In the case of Montgomery County, the change in PM_{2.5} was associated with total avoided health effects that range in value from approximately \$18 million to \$41 million. The numbers at the bottom show the totals for the current view; in this case, the totals for all of Pennsylvania.

The screenshot shows the COBRA Screening Model interface. The main window has a menu bar (File, View, Help) and a toolbar with tabs for Overview, Emissions, and Utility Reduction. Below the toolbar are sub-tabs for Air Quality, Health Effects, and Results. The Health Effects: Tables tab is active, displaying a table with columns for State, County, FIPS, \$ Total Health Effects (low), and \$ Total Health Effects (high). The table data is as follows:

State	County	FIPS	\$ Total Health Effects (low)	\$ Total Health Effects (high)
PA	Montgomery	42091	18,133,210.02	40,884.8
PA	Montour	42093	650,124.17	1,467.0
PA	Northampton	42095	11,837,631.55	26,688.1
PA	Northumberland	42097	4,045,678.25	9,157.0
PA	Perry	42099	1,584,553.52	3,582.1
PA	Philadelphia	42101	23,257,025.58	52,961.3
PA	Pike	42103	1,467,492.09	3,315.7
PA	Potter	42105	824,408.51	1,860.7
PA	Schuylkill	42107	8,074,999.88	18,271.0
			\$409,667,119.99	\$926,383.30

Below the table, there are instructions:

- To sort by column, click on the column title. To filter the data view, use the arrows on the state/county columns.
- This table presents cases of health effects avoided (in columns with blue text) and the monetary values of those benefits (in columns with black text). Any negative values indicate costs. Please refer to the User Manual for further details.
- COBRA provides two estimates of total health effects (low and high) which reflect two sets of assumptions about the sensitivity of both adult mortality and adult myocardial infarction to changes in ambient PM2.5 levels. Please refer to the User Manual for further details.

Scrolling over to the right, you can view the estimated reductions in specific health effects (shown in blue text) and their associated dollar values (shown in black text). The screenshot below shows this color-coding for respiratory-related hospital admissions.

The screenshot shows the COBRA Screening Model interface. The 'Health Effects' tab is active, displaying a table of health effects for Pennsylvania. The table includes columns for State, County, FIPS, Resp. Hosp. Adm., \$ Resp. Hosp. Adm., and CVD H. The data is as follows:

State	County	FIPS	Resp. Hosp. Adm.	\$ Resp. Hosp. Adm.	CVD H
PA	Montgomery	42091	.4079	10,860.32	
PA	Montour	42093	.0097	266.78	
PA	Northampton	42095	.3651	10,085.33	
PA	Northumberland	42097	.0811	2,254.81	
PA	Perry	42099	.0307	838.44	
PA	Philadelphia	42101	1.1842	25,466.09	
PA	Pike	42103	.0193	503.73	
PA	Potter	42105	.0192	533.43	
PA	Schuylkill	42107	.1813	4,930.51	
			10.8504	\$286,395.05	

Below the table, there are instructions:

- To sort by column, click on the column title. To filter the data view, use the arrows on the state/county columns.
- This table presents cases of health effects avoided (in columns with blue text) and the monetary values of those benefits (in columns with black text). Any negative values indicate costs. Please refer to the User Manual for further details.
- COBRA provides two estimates of total health effects (low and high) which reflect two sets of assumptions about the sensitivity of both adult mortality and adult myocardial infarction to changes in ambient PM_{2.5} levels. Please refer to the User Manual for further details.

Note that the health effects table includes low and high estimates for the changes in the number of cases and the corresponding economic values for adult mortality, non-fatal heart attacks, and total health effects. The low and high estimates are derived using two sets of assumptions about the sensitivity of adult mortality and non-fatal heart attacks to changes in ambient PM_{2.5} levels. Specifically, the high estimates are based on studies that estimated a larger effect of changes in ambient PM_{2.5} levels on the incidence of these health effects. For further details on the calculation of low and high estimates, see the description of the health effects table in Chapter 5 and the detailed assumptions in Appendix C.

We will use three health effects to demonstrate the interpretation of the change in health effects and their economic values for Montgomery County, Pennsylvania: adult mortality, non-fatal heart attacks, and respiratory hospital admissions.

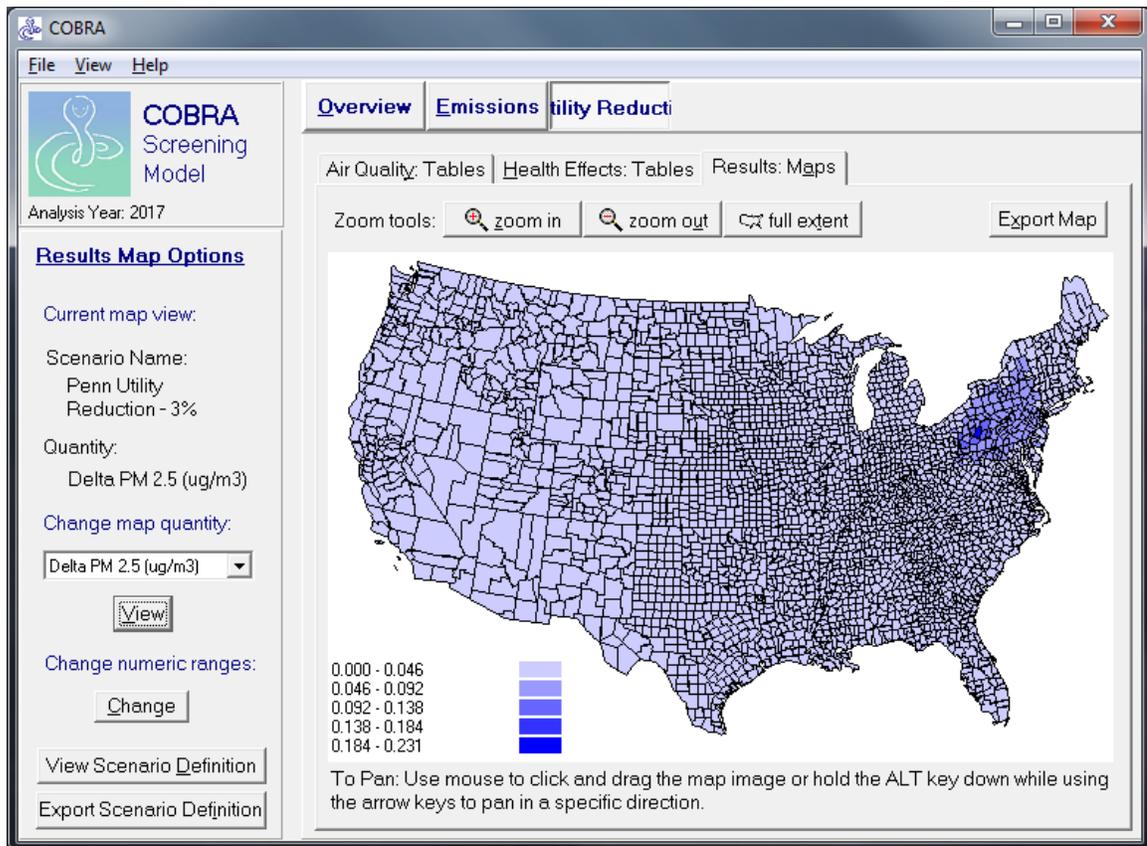
- **Respiratory Hospital Admissions.** In COBRA, most health effects and their economic values are expected to occur in the year of analysis. For instance, our scenario results in less than one avoided case of respiratory hospital admissions in Montgomery County. This avoided case and its economic value (approximately \$11,000) would occur in 2017.

- **Adult Mortality.** In contrast to respiratory hospital admissions, all avoided cases of adult mortality are not expected to occur in the year of analysis. Therefore, COBRA uses the 3% discount rate you selected in Step 4 to calculate the value of all avoided cases of adult mortality in present terms (in Montgomery County, a low estimate of approximately two avoided cases of adult mortality are valued at a total of approximately \$18 million).
- **Non-fatal Heart Attacks.** Another special case is non-fatal heart attacks. All avoided cases of non-fatal heart attacks are expected to occur in the year of analysis, but the costs associated with this health effect would occur over multiple years. Thus, while our scenario results in a range of less than one to approximately two cases of non-fatal heart attacks in 2017, all economic benefits associated with this change (\$25,000 to \$230,000) would not accrue in that same year.

In addition, remember that although we changed emissions only for Pennsylvania, COBRA calculates changes in $PM_{2.5}$ for the whole country. (However, the detectable changes are probably only in states bordering on Pennsylvania.) If you would like to examine the results for any of states bordering Pennsylvania, simply change your selection in the box in the left-hand panel and click **View**.

It is also important to remember that emissions in some states and regions are “capped” and that firms may trade emission allowances. As a result, if we assume an emission reduction among power plants in Pennsylvania, then it is likely that emissions will increase from other entities, unless the emission allowances are retired as part of the assumed emission reduction. COBRA does not automatically capture this potential effect so care should be exercised when interpreting the impacts of an emissions change in a given location.

The ‘Results: Maps’ tab shows the results from the previous two tables on a map. When you click on the tab you will see a map of the United States. The default quantity displayed is Delta $PM_{2.5}$, the change in the particulate matter concentration between the baseline and control scenarios. The darker the shade of blue, the greater the change in concentration. As in the other results tables, a positive number indicates a *decrease* from the baseline scenario.



You can also view any of the other results on the map by selected from the drop-down list under ‘Change map quantity’ and clicking **View**. You can also change the divisions in the numeric range by clicking the **Change** button under ‘Change numeric ranges’ (see Chapter 5 for details on changing the divisions).

Step 6. Export and save your results.

You may want to look at and manipulate the results data outside of COBRA. You can export small data sets into formats for use with spreadsheet programs (larger data sets can be exported into database formats). To export the health effects table for Pennsylvania into an Excel format, click on the ‘Health Effects: Tables’ tab. If the table is filtered, click the arrow next to ‘County’ and select ‘All’. Click on the **Export current data view** button. In the following window, browse to the file location where you want to save your data, and select ‘EXCEL files’ in the ‘Save as type’ drop-down box. You can then enter a name for the file in the box above; type ‘Penn Utility Reduction 2017 - 3%_health’ (COBRA will add the Excel file extension for you). Click **Save** and COBRA will save the file.

You can also save your entire results set to use again in a future COBRA session. You might want to compare it to a different scenario involving different emissions changes. At the top of the screen, click **File... Save**, and then select 'Penn Utility Reduction 2017 - 3%.' In the following window, browse to the file location where you would like to save the results file and type 'Penn Utility Reduction 2017 - 3% results.' COBRA will add a .crf (COBRA results file) extension for you. Click **Save**. To load these results in a future session, go to **File... Load** and browse to the results file you just saved.

You could then compare the results from this session to a scenario where power plants switched only ten percent of their generation to renewable sources, instead of 25%. These kinds of comparisons allow you to estimate the magnitude of the changes in health effects and benefits that result from emissions scenarios. See Appendix G for additional examples.

CHAPTER 3.

Exploring Baseline Emissions Data

The COBRA model contains detailed 2017 baseline emissions data for every county in the U.S., by state, county, tier category, and pollutant type (see Appendix A for details on the data). You can explore the emissions data for the baseline air quality scenario by clicking on the **Emissions** button in the top menu bar. You will see a screen with two tabs: ‘Base Emissions: Tables’ and ‘Base Emissions: Maps.’ Each tab is described below.

Baseline Emissions: Tables

When you click on the **Emissions** button, the information window will show a table summarizing the baseline emissions data for the U.S for the baseline air quality scenario you selected. Your year of analysis (2017) is shown at the bottom of the screen.

The default view shows emissions (in tons) by tier category and county for the entire U.S. Using the control panel at the left of the screen, you can change the table view by selecting an option in the drop-down box under ‘View new table by:.’ In the first box you can choose from the following options:

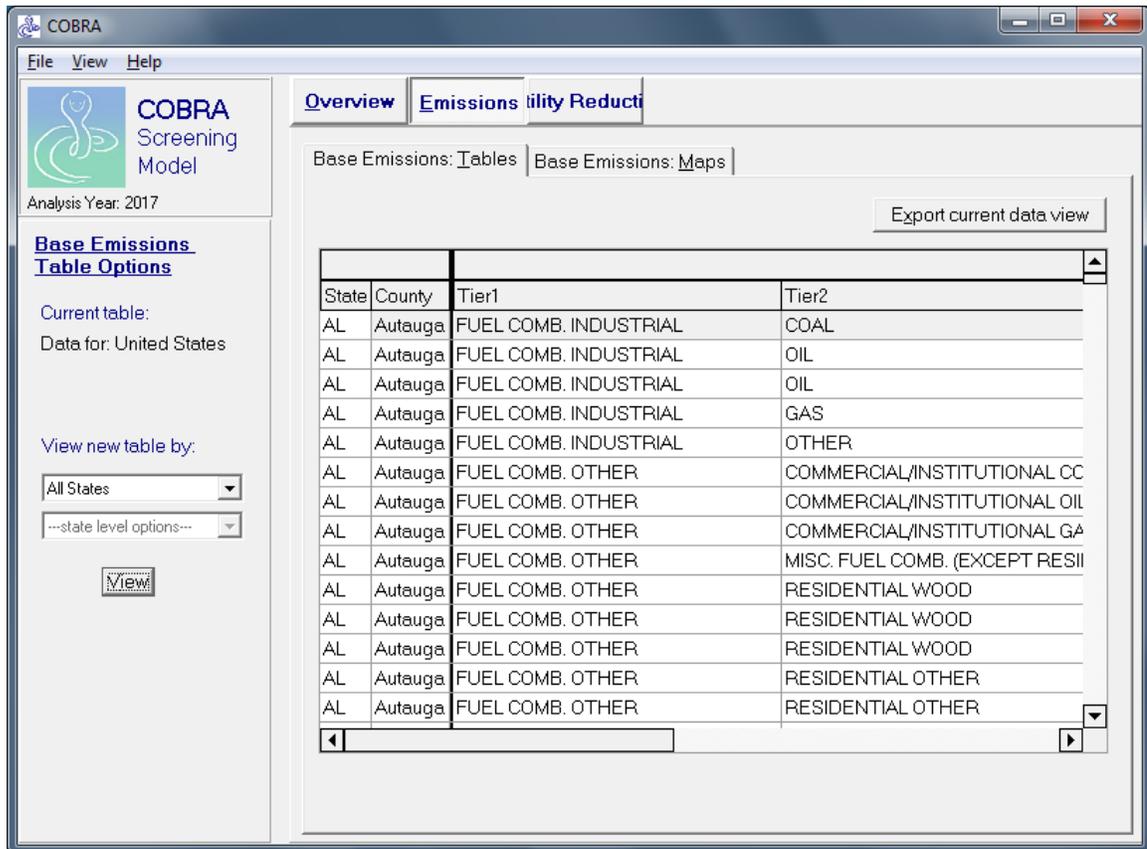
- **All States.** This view is the default, and shows the pollutants for all counties in the U.S. by tier category (in alphabetical order by state, county).
- **Individual State.** Select an individual state, click **View**, and the right-hand window will display pollutant emissions for that state, alphabetically by county. The second selection box will become active. The default selection in the second box is ‘All Counties,’ which lists pollutant values for each county in the state by tier category. Alternatively, you may select any individual county from the drop-down list to see the breakdown by tier category for that county only.

Each time you change your selection, click the **View** button to update the table display on the right. The left-hand panel displays a description of the table currently on display under ‘Current table.’ You can navigate through the table data in several ways:

Scroll through the data using the scroll bars.

Change the column order by clicking on the column name and dragging it to a new position. When you see two green arrows, you can drop the column there. Note that the sort order of the table will not change. The State and County columns will remain frozen in the view when you scroll horizontally in the table. Those two columns cannot be moved out of the frozen view, and no other columns can be added into the frozen view.

Change the width of a column by moving your mouse to the column header and pointing to the dividing line between two columns. The mouse cursor will change to two arrows, indicating that you can drag the column line to the left (to shorten) or right (to expand).



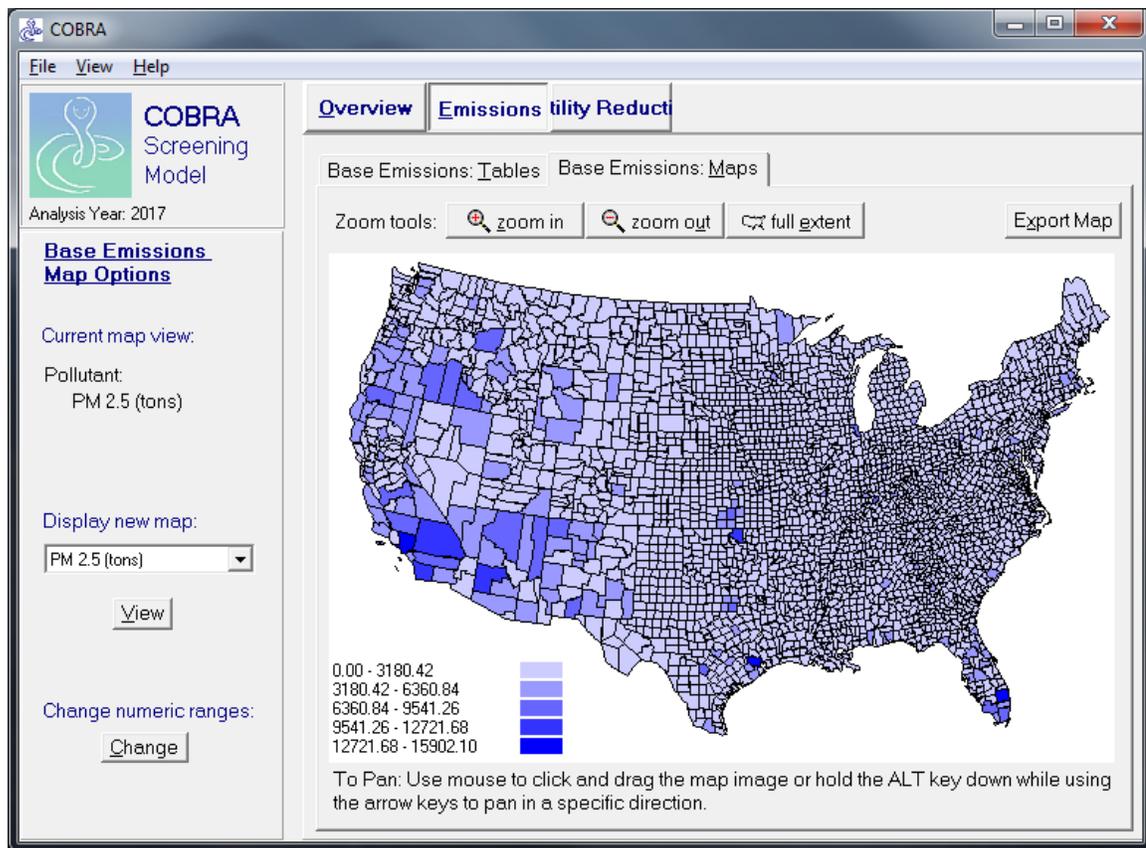
You can export the table into formats that can be read by spreadsheet and database programs by clicking on the **Export Current Data View** button. This will export only the data from the current view; to export the full baseline emissions database, make sure the current view is set to 'All States' (note that the full dataset is very large and may take a substantial amount of time to export, depending on your computer). When you click the **Export Current Data View** button, COBRA will export the table and then open the exported file using whichever program your computer has set as the default program for the file type you selected.

Exporting the emissions data is especially useful as a reference when creating a new scenario; simply open the data in a spreadsheet or database program and toggle back and forth between it and COBRA. The emissions data are very large; if you see a 'File not loaded completely' message when the file opens in your default program, then the data are too large to be completely read by that program. In this case, simply open the data in

a different program. Database programs such as Microsoft Access, Dbase, or Paradox can open larger files.

Baseline Emissions: Maps

By clicking on the Base Emissions tab, you can see the geographic distribution of pollutant concentrations in the baseline scenario. The values are mapped at the county level and show the total pollutant concentration in each county from all tier categories. You can change the pollutant being mapped by selecting a pollutant in the 'Display new map:' drop-down box.



The zoom tools across the top of the map allow you to zoom in and out, as well as return to the full extent of the map, which shows the continental U.S. Using the mouse, you can pan by clicking and dragging the map to the portion you wish to view. To zoom in on a specific area, use the right mouse button to draw a box around the area of interest.

Keyboard alternative:
Pan by holding the **ALT** key down while using the arrow keys to move in a specific direction.

The default map displays concentrations broken into five divisions based on ranges. By clicking on the **Change** button at the bottom of the control panel, you can change the number and type of numeric ranges. First enter the number of ranges that you wish to see displayed in the box at the top, and then select the type of break. The following options for the type of break are available:

- **Range.** This method takes the range of the values, and, using the number of breaks you selected, splits the range into equal intervals.
- **User Defined.** This method allows you to manually enter the upper range of each break. First select the ‘User Defined’ option, and then enter the numbers into the boxes at the right. Note that the number of breaks selected at the top determines how many boxes into which you can manually enter maximum values. The first range starts at zero and ends with the maximum value you enter in the first box (the range includes the value you enter). The next range starts with but does not include the previous maximum and ends with the maximum you enter. The maximum value must increase with each break level; the model will not accept a maximum that is lower than the previous one. The displayed values will end with the last maximum you enter, even if the range of values in the set exceeds that maximum.

Click **Apply** once you have selected the number and type of break desired, and the map display will be updated with your selections. The legend in the upper left corner describes the numeric breaks and the color used to display each division on the map. To see a range highlighted on the map, simply click on the desired row in the legend; to deselect the range, right-click on the same row. If you change the pollutant displayed, the map will use the same number and type of breaks.

You can export the currently displayed map by clicking on the **Export Map** button at the top right corner of the window. COBRA will export the map as a bitmap file, which can be viewed in many different programs including most word processors. Note that the bitmap will match the zoom level and extent currently displayed. To export a map of the entire country, click the **Full Extent** button before you export.

CHAPTER 4. Creating a New Emissions Scenario

COBRA allows users to define new emissions scenarios and investigate the related changes in air quality and health effects. You can create up to five scenarios per session, making it easy to compare outcomes between scenarios. Scenarios can also be saved and loaded back into COBRA at a later date (see the ‘Saving results’ section of Chapter 5). Additionally, the results tables and maps can be exported into various formats for future use or archiving purposes.

The steps to creating a new scenario are simple:

Step 1. Select the Geography. You can specify emissions changes at the national, state, or county level.

Step 2. Enter Emissions Changes. Changes can be made for each state or county, or the entire nation. Within each state, you can group counties and make changes to them together, or make different changes to each county.

Step 3. Run the Scenario. COBRA will calculate the changes in ambient PM_{2.5} between your selected baseline scenario and the new control scenario, and calculate the associated changes in health effects and monetary impacts.

Step 4. Examine the results. See Chapter 5.

Selecting Scenario Geography

First, select the geographic area(s) for which you would like to change emissions estimates. Click on the appropriate choice in the control panel on the left side of the **Overview** screen under ‘Scenario Options.’ Then click **Start**. The sections below describe the options for each type of run.

The geographic areas you select determine where your emissions changes are made. Your selection does not affect the geographic area for which you can see results. Regardless of the geographic area you select for emissions changes, you can see results for the entire country.

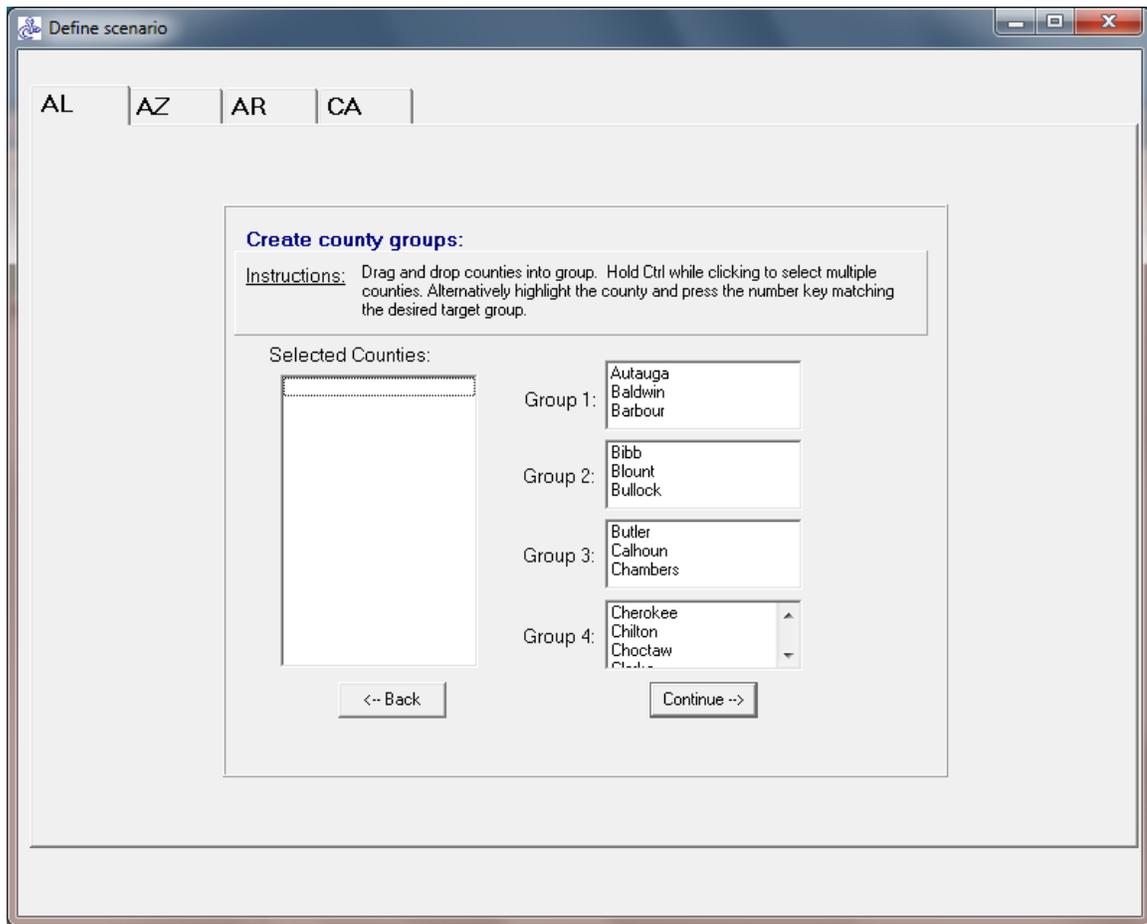
- **Nationwide.** If you select ‘nationwide,’ the model will display the emissions entry screen for your selection, where you can specify the changes that you wish to make to the baseline scenario (see ‘Defining scenario emissions’ below). The changes will be made to the emissions for the entire country.
- **Individual State.** If you wish to make emissions changes to just one state, click ‘for individual states,’ then select your state in the drop-down box and click **Start**.

The model will then ask you if you want to make changes statewide or to individual counties. If you choose ‘statewide,’ the model will take you to the emissions entry screen for your selection, where you can specify your desired changes to the baseline scenario (see ‘Defining scenario emissions’ below). The changes will be made to the emissions for the entire state. If you click ‘for individual counties’ and select only one county, you will be taken to the emissions entry screen. If you select two or more counties, you will be given the option of creating county groups before proceeding. Note that COBRA only allows you to enter individual emission changes for up to 10 counties per state. If you select more than 10 counties in a state, you must apply the same emission changes to all counties or place the counties into groups. See ‘Grouping counties,’ below.

- **Multiple States.** If you wish to make emissions changes to more than one state, click ‘for individual states’, then select your states in the drop-down box and click **Start**. The model will then display a screen with one tab for each state you selected. Each tab works separately. On each of these tabs, you must select whether you want your changes to be applied statewide or to individual counties. If you select ‘statewide’ or if you select ‘for individual counties’ and only pick one county, the model will take you to the emissions entry screen for your selection, where you can specify the changes to the baseline scenario that you wish to make (see ‘Defining scenario emissions’ below). If you select two or more counties, you will be given the option of creating county groups before proceeding. Again, note that COBRA allows you to enter individual emission changes for up to 10 counties per state; for more than 10 counties, you must apply the same changes to all selected counties or place the counties into groups. See ‘Grouping counties,’ below. **You must go through the selection process with each state tab.**

Grouping Counties

If you select three or more individual counties on the tab for any of your selected states, the model will ask if you wish to: (1) apply different changes to each individual county, (2) apply the same changes across all selected counties, or (3) group the counties into two or more (up to four) groups and define changes for each group. Selecting the first option will bring up the emissions entry screen with a tab for each selected county. You may only select the first option for up to 10 counties per state. If you select more than 10 counties in a state, you must use the second or third options. The second option will also bring up the emissions entry screen, with a tab that says ‘Group:’ and lists all of your selected counties in a single group.



If you select the third option, select the number of groups you wish to create in the drop-down box (no more than four), and click **Continue**. This will bring up a screen where you can click and drag your selected counties into boxes representing the defined groups. If you drop a county name into the wrong box, simply click and drag it into the correct one.

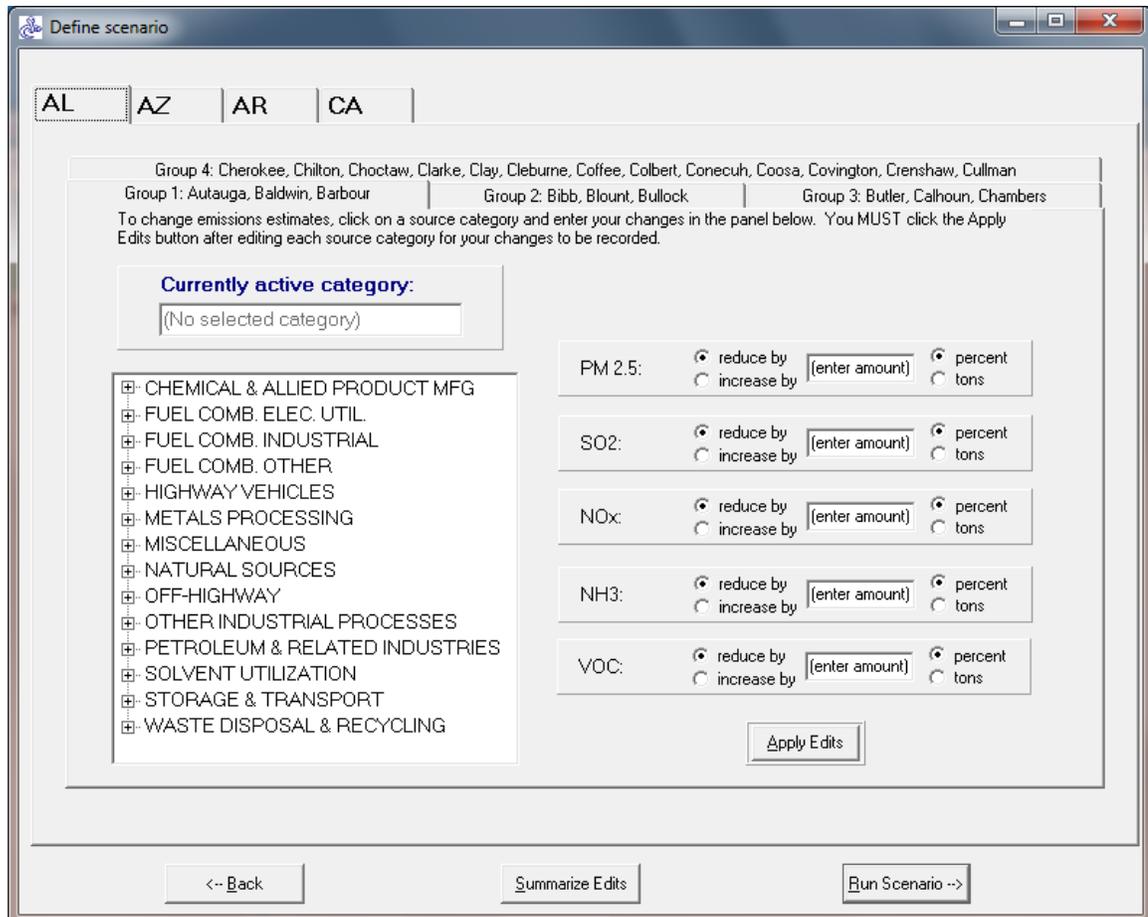
Each county must be assigned to only one group, and all counties must be assigned to groups before you can continue. If you decide you do not want to group your selected counties, simply hit the 'Back' button and change your choice. When you click **Continue** at the bottom right of the screen, the emissions entry screen will be displayed, with one tab for each group you have created.

Keyboard alternative:

Highlight a county name and then type the number of the group to which it should be assigned (e.g., for "Group 1", type 1). The county name will automatically move into that group's box.

Defining Scenario Emissions

Once you have selected your geographic areas and grouped them if appropriate, you can create a new emissions scenario by defining changes to the baseline emissions scenario. The emissions entry screen contains one tab for each state you have selected. On each state tab, there is another set of tabs for the individual or grouped counties in that state. You must enter emissions changes for each tab on each state separately.



The box on the left contains a directory tree with three levels for tier 1, 2, and 3 emissions categories (for more information about emissions categories, see Appendix A). If you hold your mouse over any of the tiers in the directory tree, a yellow box will pop up, displaying a summary of the baseline data (total tons) for each pollutant emitted by sources in that tier category for the current geographic area. If the box says ‘calculating...’, the program is still in the process of summarizing the information; the actual values will appear in a few seconds. Note that each tier category always includes all of the categories indented underneath it.

You can select a category at any tier level, then use the boxes at the right to enter changes to the baseline emissions for each of the five pollutants potentially emitted by sources in that category. You can enter emissions increases or decreases by percent or by tons in whole numbers or decimals. A change entered for a category applies to all of the branches under it, but you must enter changes individually for categories on separate branches. Click **Apply Edits** to save your changes. Once saved, the name of the edited category and any branches under it will turn blue; this will help you visually track which categories you have already modified.

Once your changes are entered for a category, you can go back to it and change it by clicking on it again in the directory tree. Your previously saved changes will be displayed in the boxes on the right when you click on the category name. At any time, you can click on the **Summarize Edits** button to see the changes you have made so far. If you have decided to apply different changes to your county groups, repeat the above steps for each tab that is visible.

If you click the **Back** button from the 'Define scenario' screen, you will be sent back to the previous screen, and any changes that you have entered (even if you have clicked the **Apply Edits** button) will be lost.

When you have made all of your desired changes, click the **Run Scenario** button at the bottom right. The model will prompt you choose a discount rate (3% or 7%) for the COBRA session. The model will then prompt you to enter the name of the scenario. Enter a name (with no extension) and click **OK**. The time to generate your results will vary, depending on the speed of your computer and on how many counties and tier categories are affected by your scenario. Once the results are generated, you will see a new button at the top with your scenario name. Click the button to view the results of your run (see Chapter 5).

CHAPTER 5.

Viewing Results

Once you have defined your new scenario (called the control scenario) and run the comparison between the baseline and your scenario, you can view the results. In this section, you can review your scenario definition and see the changes in air quality and health effects between the baseline and control scenarios. When the button with your new scenario's name is depressed, three tabs will be visible to navigate between the screens.

Viewing Scenario Definition

If you need to remind yourself of the edits you made to the baseline emissions data in order to create this scenario, click the **View Scenario Definition** button at the bottom of the 'Air Quality: Tables' tab. This will display all of your changes by tier category. If the scenario is acceptable and you wish to save it for future reference, click the **Export Scenario Definition** button. This will export a comma-delimited file that contains the same information as shown when you click the **View Scenario Definition** button. Exporting this file is especially useful if you export any other tables from the results tabs; at a later date you will have a handy reference for what the results tables and maps are based on.

Air Quality: Tables

This tab describes the changes in particulate matter concentration between the baseline emissions scenario and your scenario (the control scenario). For each county, the table lists the annual average PM_{2.5} concentration for the control scenario and the baseline scenario, as well as the change between the two scenarios (Delta PM_{2.5}). The default table view lists all counties, but you can choose any single state in the drop-down box on the left panel to limit the view to the counties in that state. You can navigate through the table data in several ways:

- **Scroll** through the data using the scroll bar on the right.
- **Change the column order** by clicking on the column name and dragging it to a new position. When you see two green arrows, you can drop the column there. Note that the sort order of the table will not change. The State and County columns will remain frozen in the view when you scroll horizontally in the table. Those two columns cannot be moved out of the frozen view, and no other columns can be added into the frozen view.

- **Change the width of a column** by moving your mouse to the column header and pointing to the dividing line between two columns. The mouse cursor will change to two arrows, indicating that you can drag the column line to the left (to shorten) or right (to expand).
- **Filter column variables** by clicking on the arrows on the FIPS (for ‘Federal Information Processing Standards’ codes), County and State columns. You can filter down to a specific state and county. The dark bar at the bottom of the table displays any filters you have defined. The filter can be turned on or off by checking the box next to it in the dark bar. You can delete a filter by clicking the ‘X’.
- **Change the sort order** by clicking on the heading of any column. Click once to sort in descending order then click again for ascending order.

The screenshot shows the COBRA Screening Model interface. On the left, there is a sidebar with the COBRA logo and 'Analysis Year: 2017'. Below this, under 'Air Quality Table Options', it shows 'Current table: Test Run', 'Scenario Name: Test Run', and 'View: Alabama'. There is a dropdown menu for 'View new table by:' set to 'Alabama' and a 'View' button. At the bottom of the sidebar are buttons for 'View Scenario Definition' and 'Export Scenario Definition'.

The main window has tabs for 'Overview', 'Emissions', and 'Test Run'. Under 'Test Run', there are sub-tabs for 'Air Quality: Tables', 'Health Effects: Tables', and 'Results: Maps'. An 'Export current data view' button is located above the table.

FIPS	County	State	Control PM 2.5	Base PM 2.5	Delta PM 2.5
01001	Autauga	AL	10.61	10.61	.0008
01003	Baldwin	AL	10.563	10.563	.0008
01005	Barbour	AL	9.833	9.834	.0007
01007	Bibb	AL	10.789	10.79	.0008
01009	Blount	AL	10.134	10.135	.0007
01011	Bullock	AL	10.412	10.413	.0006
01013	Butler	AL	9.986	9.987	.0008
01015	Calhoun	AL	9.71	9.71	.0006
01017	Chambers	AL	10.33	10.33	.0007
01019	Cherokee	AL	9.784	9.785	.0007
01021	Chilton	AL	10.672	10.673	.0008
01023	Choctaw	AL	10.77	10.771	.0009
01025	Clarke	AL	10.763	10.764	.0009
01027	Clay	AL	9.927	9.928	.0007

At the bottom of the table, there is a note: 'Data estimates for 2017. All values are in ug/m3. To sort by column, click on the column title. To filter the data view, use the arrows on the state/county columns. A positive value indicates a decrease from the base scenario.'

Note that if you have run a state-specific scenario, changes in air quality for other states will typically decrease as the distance from the state increases, since the emissions changes were only made there. You can export the table by clicking on the **Export Current Data View** button. This will export only the data from the current table; to export the full air quality data set, make sure the current table shows ‘All States.’

Health Effects: Tables

This tab displays the change in the number of cases for each health effect between the baseline emissions scenario and your scenario. These changes are derived using the health impact functions described in Appendix C. For each health effect, the table also displays an estimate of the economic value of the change in the number of cases. For more information, see Appendix F. Exhibit 2 describes the health endpoints and valuations that are included in the health effects tables in COBRA.

Exhibit 2. Description of Health Effects and their Economic Values

Health Effect	Description
Total Health Effects\$ (Low)	Economic value of all health effects combined in Low Case, using a discount rate of 3% or 7%
Total Health Effects\$ (High)	Economic value of all health effects combined in High Case, using a discount rate of 3% or 7%
Adult Mortality (Low)	Low estimate of the number of deaths, based on Krewski et al. (2009)
Adult Mortality \$ (Low)	Low estimate of the economic value of the number of deaths, using Krewski et al. (2009) and a discount rate of 3% or 7%
Adult Mortality (High)	High estimate of the number of deaths, based on Lepeule et al. (2012)
Adult Mortality \$ (High)	High estimate of the economic value of the number of deaths, using Lepeule et al. (2012) and a discount rate of 3% or 7%
Infant Mortality	Number of infant deaths
Infant Mortality \$	Economic value of the number of infant deaths
Non-fatal Heart Attacks (Low)	Low estimate of the number of non-fatal heart attacks, based on four acute myocardial infarction (AMI) studies
Non-fatal Heart Attacks \$ (Low)	Low estimate of the economic value of non-fatal heart attacks, based on four AMI studies and a discount rate of 3% or 7%
Non-fatal Heart Attacks (High)	High estimate of the number of non-fatal heart attacks, based on Peter et al. (2001)
Non-fatal Heart Attacks \$ (High)	High estimate of the economic value of non-fatal heart attacks, using Peter et al. (2001) and a discount rate of 3% or 7%
Resp. Hosp. Adm.	Number of respiratory-related hospitalizations (e.g., all respiratory, asthma and COPD)
Resp. Hosp. Adm. \$	Economic value of respiratory-related hospitalizations
CVD Hosp. Adm.	Number of cardiovascular-related hospitalizations (ICD codes 390-409, 411-429). ICD code 410 (nonfatal heart attacks) is counted only in 'Non-fatal Heart Attacks'

Health Effect	Description
CVD Hosp. Adm. \$	Economic value of cardiovascular-related hospitalizations
Acute Bronchitis	Cases of acute bronchitis
Acute Bronchitis \$	Economic value of acute bronchitis cases
Upper Resp. Symptoms	Episodes of upper respiratory symptoms (runny or stuffy nose; wet cough; and burning, aching, or red eyes)
Upper Resp. Symptoms \$	Economic value of episodes of upper respiratory symptoms
Lower Res. Symptoms	Episodes of lower respiratory symptoms: cough, chest pain, phlegm, or wheeze
Lower Res. Symptoms \$	Economic value of episodes of lower respiratory symptoms
Asthma ER Visits	Number of asthma-related emergency room visits
Asthma ER Visits \$	Economic value of asthma-related emergency room visits
MRAD	Number of minor restricted activity days (days on which activity is reduced, but not severely restricted- e.g. missing work or being confined to bed is too severe to be MRAD).
MRAD \$	Economic value of minor restricted activity days
Work Loss Days	Number of work days lost due to illness
Work Loss Days \$	Economic value of work days lost due to illness
Asthma Exacerbations	Shortness of breath, wheeze, and cough (in asthmatic individuals)
Asthma Exacerbations \$	Economic value of episodes of asthma exacerbations

Notes: * For adult mortality and non-fatal heart attacks, COBRA contains multiple health impact functions that relate PM_{2.5} and each health effect. Therefore, there are high and low estimates of the cases avoided and their economic values for each of these health effects. The high and low estimates of the economic value of total health affects avoided are based on the corresponding high and low estimates for adult mortality and non-fatal heart attacks, along with the single estimates for all other health effects. More details on the underlying health impact functions are available in Appendix C of the user manual. In addition, future costs are calculated using a discount rate (3% or 7%) that you selected before running the scenario.

The health effects table includes low and high estimates for the changes in the number of cases and the corresponding economic values for adult mortality, non-fatal heart attacks, and total health effects. The low and high estimates are derived using two sets of assumptions about the sensitivity of adult mortality and non-fatal heart attacks to changes in ambient PM_{2.5} levels. Specifically, the high estimates are based on studies that estimated a larger effect of changes in ambient PM_{2.5} levels on the incidence of these health effects. The low and high estimates for each of these values are derived as follows:

- **Adult Mortality.** EPA (2009) recently used two studies when analyzing proposed NO₂ national ambient air quality standards; EPA presented the results separately

for each study. Following EPA, COBRA reports the results of two health impact functions that relate $PM_{2.5}$ and mortality: Krewski et al. (2009) and Lepeule et al. (2012). In the health effects table, **Adult Mortality (Low)** and **Adult Mortality \$ (Low)** represent estimates of deaths avoided and their economic value, respectively, based on Krewski et al. (2009). **Adult Mortality (High)** and **Adult Mortality \$ (High)** represent estimates of deaths avoided and their economic value, respectively, based on Lepeule et al. (2012). More details on the two studies are available in Appendix C of the user manual.

- **Non-fatal Heart Attacks.** COBRA calculates two estimates of the non-fatal heart attack cases avoided (**Non-fatal Heart Attacks**) and their economic value (**Non-fatal Heart Attacks \$**). The low estimate is based on Peter et al. (2001), while the high estimate is based on pooling of the effect estimates of the following four studies: Sullivan et al. (2005), Pope et al. (2006), Zanobetti et al. (2009), and Zanobetti & Schwartz (2006). More details on the studies are available in Appendix C of the user manual.

Total Health Effects. The **Total Health Effects \$ (Low)** includes estimates based on Krewski et al. (2009) for adult mortality and Peter et al. (2001) for non-fatal heart attacks, along with the single estimates for all other health effects. Similarly, **Total Health Effects \$ (High)** includes estimates based on Lepeule et al. (2012) for adult mortality and pooling of the effect estimates of the four studies listed above for non-fatal heart attacks, as well as the single estimates for all other health effects.

The value in each health effects column represents the total change in the number of cases of each health endpoint in a county. A value of 3.00 in the Adult Mortality (low) column, for instance, indicates that in your scenario there would be an estimated 3 fewer cases of premature mortality compared to the baseline emissions scenario. *Note, however, that a negative number signifies an increase in cases.* Therefore, - 3.00 in the Adult Mortality (low) column indicates that in your scenario there would be 3 additional cases of premature mortality compared to the baseline emissions scenario.

Interpreting positive and negative results:

In the health effects table, positive numbers indicate reductions in the number of cases of adverse health effects and the associated monetary benefits of your scenario. Negative numbers signify increases in the number of cases of health effects and the resulting costs.

The screenshot shows the COBRA Screening Model interface. The main window displays a table of health effects data for Alabama counties. The table has columns for State, County, FIPS, \$ Total Health Effects (low), and \$ Total Health Effects (high). The data is as follows:

State	County	FIPS	\$ Total Health Effects (low)	\$ Total Health Effects (high)
AL	Autauga	01001	20,419.16	46.2
AL	Baldwin	01003	83,636.93	189.1
AL	Barbour	01005	9,764.55	22.1
AL	Bibb	01007	8,942.93	20.2
AL	Blount	01009	20,578.33	46.5
AL	Bullock	01011	3,850.83	
AL	Butler	01013	9,257.43	20.9
AL	Calhoun	01015	40,354.78	91.5
AL	Chambers	01017	14,821.07	33.4
			\$117,395,091.4	\$265,606.4

Below the table, there are instructions:

- To sort by column, click on the column title. To filter the data view, use the arrows on the state/county columns.
- This table presents cases of health effects avoided (in columns with blue text) and the monetary values of those benefits (in columns with black text). Any negative values indicate costs. Please refer to the User Manual for further details.
- COBRA provides two estimates of total health effects (low and high) which reflect two sets of assumptions about the sensitivity of both adult mortality and adult myocardial infarction to changes in ambient PM_{2.5} levels. Please refer to the User Manual for further details.

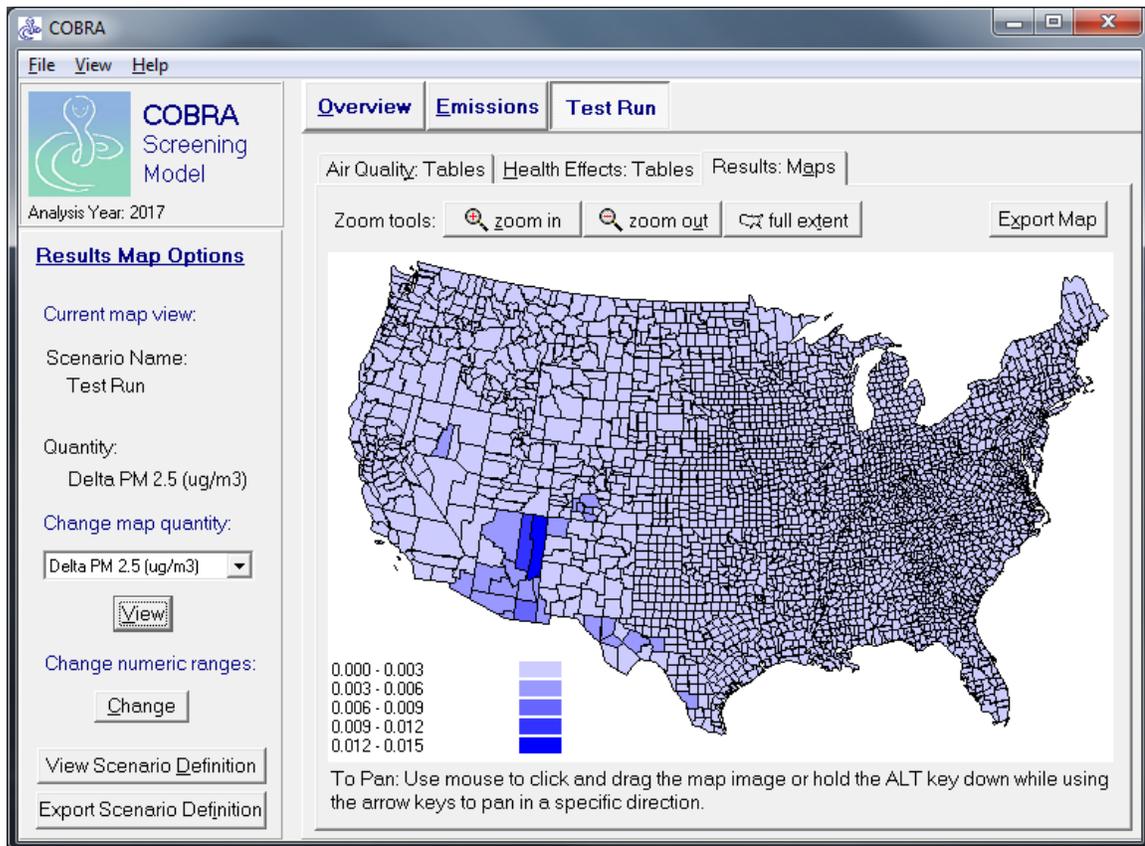
The values in grey at the bottom of each column are the subtotals for the view that is currently displayed in the table; therefore, to see the total national effect, be sure to set your table view to ‘All States.’ Each row in the table represents the overall impact on the entire population living in each county, so the number of adverse health effects can be fairly large, particularly for the less severe health effects, such as work loss days (WLDs) and minor restricted activity days (MRADs).

All health effects are monetized. However, to prevent double-counting, the calculation of asthma exacerbations only includes asthma effects occurring in children aged 6-18 years. This approach follows the recommendations of EPA’s Science Advisory Board Health Effects Subcommittee (SAB-HES) for valuing asthma exacerbations, as described in the benefits analysis for the 2006 Regulatory Impact Analysis for the revised PM_{2.5} National Ambient Air Quality Standard (U.S. EPA, 2006). Studies of the general population include asthmatics, so estimates based solely on the adult asthmatic population cannot be directly added to the general population numbers without double-counting. Instead, asthma exacerbations occurring in adults were assumed to be accounted for in health effects for the general population, such as WLDs and MRADs (U.S. EPA, 2006). Since the health effects for the general population do not include asthma effects in children, the analysis of asthma exacerbations for children does not lead to double-counting (see Appendix C for details).

As in the 'Air Quality: Tables' screen, you can select different state views for your table using the options in the lower left panel and filter the view down to the county level using the arrows in the table columns. By clicking on the heading of any column you can sort the table by that column. Click once to sort in descending order then click again for ascending order. To go back to the default sort order, click on the first column. You can also export the table to a comma-delimited file using the button at the top right of your screen. See 'Air Quality: Tables' above for more detail.

Results: Maps

This screen displays the results of your scenario geographically. The left side of the screen allows you to change the values shown on the map. You can display the change in $PM_{2.5}$ between your scenario and the baseline emissions (the same values shown as 'Delta $PM_{2.5}$ ' in the 'Air Quality: Tables' screen), or any of the health endpoints included in the model. The values displayed for each health endpoint are the change in the number of cases (or deaths for 'Adult Mortality (Low)', 'Adult Mortality (High)', and 'Infant Mortality') and the economic valuation of these cases from the scenario, as displayed in the 'Health Effects: Tables' screen. Note that if your scenario represents an increase in cases, the values are negative and are therefore displayed in parentheses on the map legend.

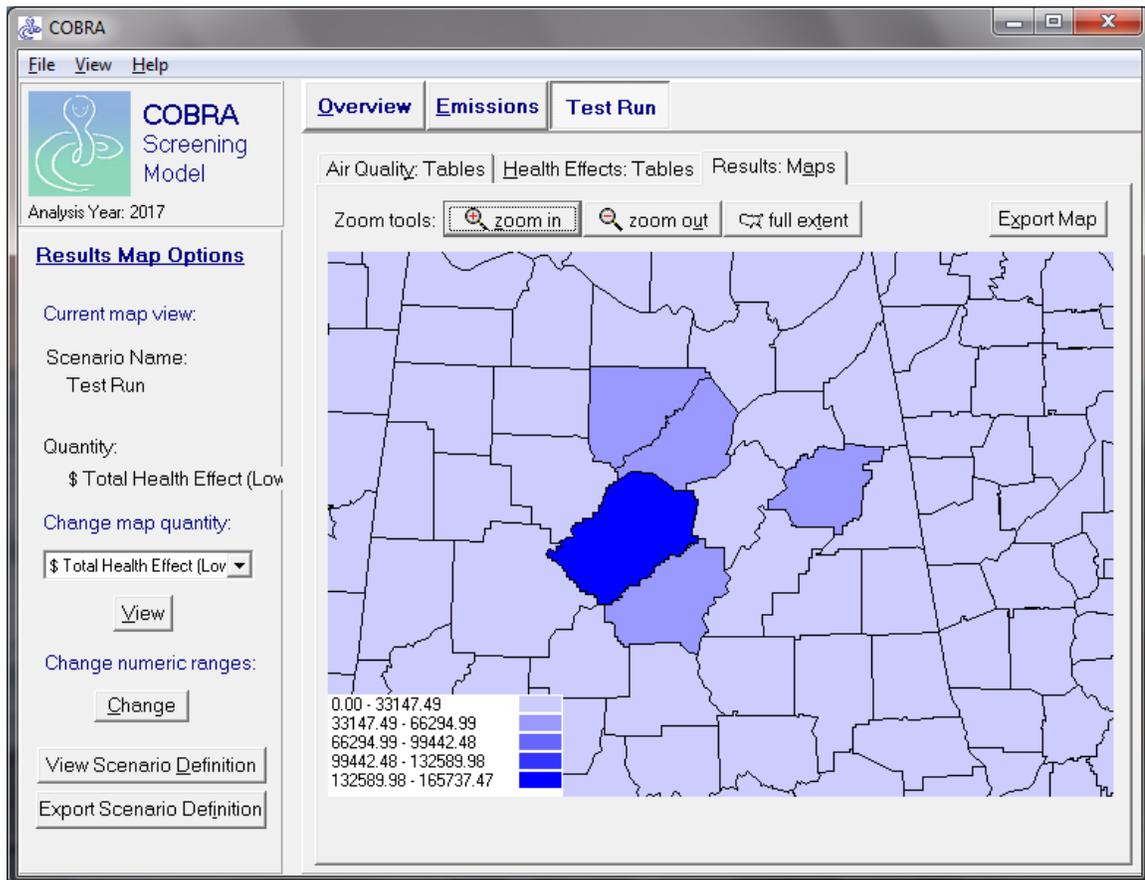


You can select one of two options for your map's numeric breaks:

- **Range.** This method takes the range of the values, and, using the number of breaks you selected, splits the range into equal intervals.
- **User Defined.** This method allows you to manually enter the upper range of each break. First select the 'User Defined' option, then enter the numbers into the boxes at the right, using a minus sign (rather than parentheses) if you are dealing with negative numbers. Note that the number of breaks selected at the top determines how many boxes into which you can manually enter maximum values. For positive numbers, the first range starts at zero and ends with the maximum value you enter in the first box (the range includes the value you enter). For negative values, the first break starts at the smallest value for the health effect or $PM_{2.5}$ that you are mapping. The next range starts with, but does not include, the previous break's maximum and ends with the maximum you enter. The maximum value must increase with each break level; the model will not accept a maximum that is lower than the previous one. The displayed values will end with the last maximum you enter, even if the range of values in the set exceeds that maximum.

The zoom tools at the top left of the screen allow you to zoom in and out in the map. You can also pan by clicking and dragging the map to the portion you wish to view (or from

the keyboard, use the ALT key plus arrow keys to indicate the direction to pan). You can zoom in on a specific area by drawing a box with right mouse button depressed. Click on **Full Extent** to zoom to full U.S. view. To highlight a range of values on the map, simply click on the desired row in the legend; to deselect it, right click on the same row. The highlighted data will be yellow.



You can export the map as currently displayed to a bitmap file by clicking on the **Export Map** button at the top right. The bitmap file will show the map and the legend only; what is being mapped and the scenario name will not be visible, so it is advisable that you incorporate that information into the file name.

Saving Results

There are several options for saving your results. You can save the entire scenario for future use within COBRA by clicking on **File... Save** and then selecting the scenario from the list. This will store the scenario definition and results in a COBRA Results File (.crf) format. If you want to use the scenario results in a future COBRA session, use the **File... Load** option. You will see the loaded scenario appear as a button at the top of the screen.

To save your results for use outside of the COBRA environment, you can export the air quality and health effects tables (see ‘Viewing Scenario Results’ above). The maps can also be customized within COBRA and then exported into bitmap format for use in documents and presentations.

Glossary

Baseline scenario: The emissions estimates for 2017 in absence of a policy, ambient pollution levels and health impacts for 2017. The baseline scenario is compared to the control scenario when running COBRA.

Control scenario: A hypothetical scenario that factors in user-specified emissions changes (to ‘control’ emissions). In COBRA, the control scenario is compared to the baseline scenario.

Delta PM_{2.5}: The difference in ambient concentrations of particulate matter that is less than or equal to 2.5 microns in diameter.

Health impact function: An equation that calculates the change in adverse health effects associated with a change in exposure to air population. A typical health impact function has inputs specifying the change in the air pollutant, an effect coefficient (specifying the percent change in an adverse health effect per unit change of a pollutant), the age of the population affected, and the incidence rate of the adverse health effect.

Mercury and Air Toxics Standards (MATS) Final Rule: An EPA regulation issued in December 2011 to limit mercury and other toxic air pollution from coal and oil-fired power plants. For more information on the rule, see <http://www.epa.gov/airquality/powerplanttoxics/actions.html>.

Scenario definition: A table of all edits made to the baseline emissions when defining a control scenario. The table can be viewed within COBRA or can be exported for future reference.

Sensitivity analyses: Comparison of analyses performed with varied assumptions or decisions to determine whether the assumptions/decisions have a major effect on the results of the analysis.

Source-receptor matrix: An air quality model built into COBRA that calculates the change in PM_{2.5} levels for any given change in emissions. Appendix A discusses this model in more detail.

Tier category: Classification used by EPA for emission inventories. Additional information on tier categories is available at: <http://www.epa.gov/ttn/chief/codes/>

APPENDICES

Appendix A: Dispersion Modeling in COBRA

COBRA estimates particulate matter levels using the Phase II Source-Receptor (S-R) Matrix. The S-R Matrix consists of fixed transfer coefficients that reflect the relationship between annual average PM_{2.5} concentration values at a single receptor in each county (a hypothetical monitor located at the county centroid) and the contribution by PM_{2.5} species to this concentration from each emission source (E.H. Pechan & Associates Inc., 1994).

Levy et al. (2003) found that an earlier version of the S-R Matrix predicted public health benefits that were similar to those predicted by CALPUFF, a comparatively more sophisticated model often used in risk assessments. Using the emission impacts from seven power plants in northern Georgia, Levy et al reported that the two models yielded generally similar results for sulfates or primary PM_{2.5}, with somewhat greater differences for nitrates. However, they carefully noted that this result may differ depending on the location of the emissions, as temperature and humidity are important considerations in the formation of ambient particles.

Because of the limited validation studies of the S-R Matrix, it should be treated as a screening tool that provides a crude estimate of the likely impact of a change in emissions on ambient PM_{2.5} levels. More sophisticated atmospheric dispersion models should be used to obtain detailed estimates of ambient air quality changes.

The sections below summarize the development of the S-R matrix and the steps taken to apply the matrix in COBRA in order to derive the changes in air quality resulting from changes in emissions.

Development of the S-R Matrix

The S-R matrix is based on the Climatological Regional Dispersion Model (CRDM), which uses assumptions similar to the Industrial Source Complex Short Term model (ISCST3), an EPA-recommended short range Gaussian dispersion model (U.S. EPA, 1995). The CRDM incorporates terms for wet and dry deposition of primary and secondary species that constitute PM_{2.5} and uses meteorological summaries (annual average mixing heights and joint frequency distributions of wind speed and direction) from 100 upper air meteorological sites throughout North America. This analysis employs meteorological data collected in 1990.

Relative to more sophisticated and resource-intensive three-dimensional modeling approaches, the CRDM does not fully account for all the complex chemical interactions that take place in the atmosphere in the secondary formation of PM_{2.5}. Instead it relies on more simplistic species dispersion-transport mechanisms supplemented with chemical conversion at the receptor location.

The CRDM uses Turner's sector-average approach (Turner, 1970), a probabilistic method in which relative frequencies of occurrence of combinations of wind and stability conditions at the emissions source are used to calculate the relative frequencies of transport in various sectors.

This method is recommended for the estimation of long-term average pollutant concentrations (E.H. Pechan & Associates Inc., 1997).

The pollutant concentration in a destination sector is estimated as follows:

$$C_j(r) = \frac{2Q(r)}{y\sqrt{2\pi}} \sum_{i,k} \frac{f_{i,j,k}}{u_i \sigma_{z,k}} \exp\left[-\frac{1}{2}\left(\frac{H}{\sigma_{z,k}}\right)^2\right] \quad (1)$$

where:

$C_j(r)$ = atmospheric concentration in destination sector j at distance r

$Q(r)$ = pollutant mass flux at distance r

y = sector width at distance r

$f_{i,j,k}$ = joint frequency of wind speed class i , wind direction j , and stability category k

$\sigma_{z,k}$ = vertical diffusion coefficient for stability category k

u_i = wind speed for wind class i

H = effective stack height of emissions source (= 0 for ground-level sources)

The sector width is calculated as:

$$y = \left(\frac{2\pi}{16}\right)r \quad (2)$$

Primary emissions from a county are assumed to always impact the county source county itself and are evenly distributed over a square with the same area as the county. A simple box model is used for each combination of wind speed and stability category. The vertical diffusion coefficient, σ_z , is then calculated at a downwind distance corresponding to the side of the square.¹ These assumptions are necessary since the spatial variation of emissions within a county cannot be provided for a national scale model.²

Additional adjustments are made to ensure a consistent distribution of pollutant species among areas in close proximity to the emissions source. Receptors at a distance less than the square root of the source area are assumed to receive the same concentration of pollutants as the source area.

¹ The vertical diffusion coefficient σ_z was calculated using a subroutine from EPA's ISC3 model. Atmospheric stabilities were assumed to be *C* class (slightly unstable) during the day and *E* class (slightly stable) at night. However, for wind speeds in excess of 6 m/s, stability was assumed to be neutral (class *D*).

² Actual measured concentrations would be expected to be higher than those modeled with these assumptions for a monitor located in, or generally downwind from, a portion of the county with emission densities much higher than the county average. On the other hand, concentrations would be expected to be lower if a monitor is located at the prevailing upwind edge of the county or in an area of relatively low emission density.

In addition, the destination sector width is constrained to be at least equal to the square root of the source area.

Equation (1) is applicable to both point and area sources, either ground-level or elevated, and results in a Gaussian distribution of pollutant mass in the vertical dimension. However, for long-range transport, emissions are distributed uniformly in the vertical between the top of the mixed layer and the ground. This occurs when the vertical diffusion parameter, σ_z , is equal to the height of the mixed layer, h_m . For such long-range situations, the sector-average limited mixing model of Turner (1970) estimates pollutant concentrations at a downward distance r from the source as:

$$C_j(r) = \frac{Q(r)}{h_m y} \sum_{i,k} \frac{f_{i,j,k}}{u_i} \quad (3)$$

The mass flux of a directly emitted primary species at distance r from the source is a function of the material initially emitted, the amount chemically converted to a secondary pollutant, and the amount deposited by wet and dry processes during the period of transport (time t) from the emission point to the receptor. This is calculated by solving the relevant differential equation (Latimer, 1993):

$$Q_p(t) = Q_0 e^{-(k_c + k_p)t} \quad (4)$$

where:

- $Q_p(t)$ = primary pollutant mass flux at transport time t
- Q_0 = initial emission rate
- k_c = pseudo-first-order rate constant for chemical conversion of the primary species to the secondary species
- k_p = pseudo-first-order rate constant for deposition of primary species, equal to the sum of the dry and wet deposition rate constants ($k_{pd} + k_{pw}$)
- t = transport time

The mass flux of secondary pollutants is dependent upon the fraction of the primary species that is chemically converted in the atmosphere to the secondary species and the amount of the secondary species that is deposited by wet and dry deposition processes during the transport time t from the stack to the downwind receptor point at distance r . This is also calculated by solving the relevant differential equation (Latimer, 1993):

$$Q_s(t) = \frac{k_c Q_0}{k_c + k_p - k_s} \left(e^{-k_s t} - e^{-(k_c + k_p)t} \right) \quad (5)$$

where:

- $Q_s(t)$ = mass flux of the secondary species at transport time t

- Q_0 = initial emission rate
- k_c = pseudo-first-order rate constant for chemical conversion of the primary species to the secondary species
- k_p = pseudo-first-order rate constant for deposition of primary species, equal to the sum of the dry and wet deposition rate constants ($k_{pd} + k_{pw}$)
- k_s = pseudo-first-order rate constant for deposition of secondary species, equal to the sum of the dry and wet deposition rate constants ($k_{sd} + k_{sw}$)
- t = transport time

The model parameters used to estimate mass flux are detailed in Exhibit A-1. Note that the pseudo-first-order rate constant for deposition, k_p , is estimated from the dry and wet deposition velocities by dividing them by the mixing height (h_m).

Exhibit A-1. Pollutant-specific Model Parameters

	PM _{2.5} , SOA *	SO ₂ **	NO ₂	NH ₃
Chemical Conversion Rate, k_c (%/hr) [RH = relative humidity (%)]	0	0.5 if RH < 40 1.5 if RH > 70 ((RH - 40)/30) + 0.5 Otherwise	2	0
Dry Deposition Velocity (cm/s)	0.1	0.5	1	1
Wet Deposition Velocity (cm/s)*** [P = annual precipitation rate (in.)]	0.01 P	0.003 P	0.0003 P	0.0003 P

* Secondary organic aerosols.

** The chemical conversion rate for SO₂ was parameterized as a function of relative humidity to account for greater atmospheric conversion rates in areas of the country with higher humidity.

*** Wet deposition velocities are from (Yamartino, 1985).

Details of S-R Matrix Implementation in COBRA

In subsections below we provide the following implementation details on: (i) processing of the EPA's emissions data to create COBRA emissions baseline; (ii) meteorological data sources and processing; (iii) generating S-R transfer coefficients; (iv) approach taken to model secondary PM_{2.5} formation (atmospheric chemistry); and (v) calibration of dispersion model outputs to the monitored PM_{2.5}.

Emissions Data

We use emissions data from the control case of the EPA's Mercury and Air Toxics Standards Final Rule³ (hereafter, the MATS rule) to forecast ambient 2017 PM_{2.5} levels in COBRA.⁴ The assumptions underlying the emission inventories are detailed in the Emissions Modeling for the Final Mercury and Air Toxics Standards Technical Support Document (U.S. EPA, 2011). The 2017 control case developed by EPA for the MATS rule includes:

- electrical generating unit emissions (reflecting the implementation of both MATS and the Cross-State Air Pollution Rule),⁵
- mobile emissions (reflecting the impacts of implementation of the Energy Independence and Security Act of 2007 and the Energy Policy Act of 2005 on mobile source fuels), and
- average year fire data.

In addition to the 2017 control case emission inventories for the MATS rule, we used a 2005 base case emissions inventory to help develop calibration factors (discussed in more detail in a later section). Exhibit A-2a and Exhibit A-2b summarize the 2005 and 2017 emissions data for the continental U.S. that we used.

³ 77 FR 9304-9513

⁴ Note that 2005 county-level natural emissions (from plants and soil) and were estimated using the BEIS 3.12 model (U.S. EPA, 2003a).

⁵ On August 21, 2012, the U.S. Court of Appeals for the D.C. Circuit issued an opinion that would vacate the Cross State Air Pollution Rule. On October 5, 2012 the United States filed a petition seeking rehearing of that decision. Further information about CSAPR (77 FR 34830) is available at: <http://www.epa.gov/airtransport/>.

Exhibit A-2a. 2005 Emissions Inventory Summary, by Tier 1 (tons/year)

Tier 1	NO₂	SO₂	PM_{2.5}	VOC	NH₃
Fuel Combustion Electric Utilities	3,606,858	10,247,563	494,069	37,133	17,849
Fuel Combustion Industrial	487,117	689,195	85,972	18,493	12,609
Fuel Combustion Other	623,336	477,948	409,684	573,465	16,294
Chemical & Allied Product Manuf.	63	9	24	114,430	61
Metals Processing	85	45	85	464	5
Petroleum & Related Industries	449,228	10,187	4,853	911,027	
Other Industrial Processes	12,106	6,207	214,009	51,510	59,857
Solvent Utilization	111	23	1,683	3,912,489	59
Storage & Transport	7,297	172	448	1,384,849	22
Waste Disposal & Recycling	66,712	10,795	253,681	366,801	22,673
Highway Vehicles	8,233,725	168,452	301,030	3,267,313	144,381
Off-Highway Vehicles	3,953,869	349,313	258,049	2,873,916	2,743
Natural Sources	1,060,915			31,695,823	
Miscellaneous	255,686	70,645	1,823,717	2,184,552	3,312,043
Total	18,757,108	12,030,555	3,847,303	47,392,264	3,588,597

Exhibit A-2b. 2017 Emissions Inventory Summary, by Tier 1 (tons/year)

Tier 1	NO₂	SO₂	NH₃	PM_{2.5}	VOC
Fuel Combustion Electric Utilities	1,788,581	1,874,027	34,165	223,168	41,353
Fuel Combustion Industrial	455,286	669,180	11,754	84,980	15,527
Fuel Combustion Other	588,335	404,129	12,482	203,589	265,831
Chemical & Allied Product Manuf.	64,125	4,982	62	24	119,767
Metals Processing	85	45	5	85	464
Petroleum & Related Industries	445,567	492		3,241	1,162,367
Other Industrial Processes	11,796	2,944	59,797	217,227	107,299
Solvent Utilization	111	23	59	1,683	3,863,540
Storage & Transport	7,297	172	22	447	1,055,120
Waste Disposal & Recycling	66,711	10,795	22,673	253,677	346,884
Highway Vehicles	3,204,285	29,282	85,362	129,392	1,397,412
Off-Highway Vehicles	2,443,196	9,878	3,359	148,006	1,556,261
Natural Sources	1,060,915				31,695,823
Miscellaneous	255,686	70,645	3,565,464	1,830,393	2,188,495
Total	10,391,977	3,076,594	3,795,204	3,095,911	43,816,143

We estimate the formation of SOA using a fixed relationship between SOA and VOC for each Tier 3 emission category.⁶ The inventory for the MATS rule estimated VOC but did not estimate SOA, so we developed a simple approach to estimate the conversion of VOC to SOA, though this conversion actually depends upon a number of factors including climate and the type of VOC. We used the 2010 base case inventory of SOA and VOC emissions generated for the Clear Skies Act (CSA) of 2003 (U.S. EPA, 2003b). For each Tier 3 emission category in this inventory, we calculated the ratio of SOA to VOC. We then used these Tier 3 category-specific ratios to estimate SOA in the MATS emissions inventory:

$$SOA_{\text{MATS, Tier 3}} = VOC_{\text{MATS, Tier 3}} \cdot \left(\frac{SOA_{\text{CSA, Tier 3}}}{VOC_{\text{CSA, Tier 3}}} \right)$$

When modeling emission sources, we categorized them into elevated point sources and area/mobile sources. For each, we calculate an “effective stack” height, which takes into account the actual stack height, gas temperature and velocity, stack diameter, and other factors. The effective stack height is important as it is one of the greatest determinants⁷ of how far emissions will disperse – generally the taller the effective stack the further the emissions might travel from the source. In calculating effective stack height, we assume an average wind speed of 5 meters per second using the plume rise algorithm from ISCST3 (U.S. EPA, 1995).

We group stationary point source emissions for each county into three groups based on effective stack height: (1) less than 250 meters, (2) 250 to 500 meters, and (3) greater than 500 meters. We assume that emissions from the two groups less than 500 meters originate from the center of the county in which they are located. For point sources with effective stack heights greater than 500 meters, we use their true latitude and longitude coordinates when modeling the dispersion of emissions.⁸

Emissions from both ground-level mobile and area sources in the contiguous U.S. are combined at the county-level and modeled as emissions from stacks with an effective stack height of zero located at the source county centroid. Exhibit A-3 summarizes these emission categories.

⁶ The emissions inventory in COBRA has fourteen broad Tier 1 categories (e.g., on-road motor vehicles), and within each of these larger categories there are Tier 2 (e.g., diesels), and Tier 3 (e.g., heavy duty diesels) categories.

⁷ The other determinants include wind speed and direction as well as atmospheric chemistry.

⁸ For some counties, the emissions inventory contained more than one emission source with stack height greater than 500m. These emission sources normally have different locations and stack heights. To create a composite county-level emissions source with stack height greater than 500m, we used the latitude and longitude of the source with the tallest stack, whereas the composite stack height was an emissions-weighted average.

Exhibit A-3. Emissions Categories for the S-R Matrix

Emissions Category	Effective Stack Height	Modeled Location
U.S. area and mobile emissions	0 m	County center
U.S. elevated point emissions	0-250 m	County center
U.S. elevated point emissions	250-500 m	County center
U.S. elevated point emissions	>500 m	True location

Meteorological Data

Meteorological variables were calculated from rawinsonde data on the NAMER-WINDTEMP tapes⁹ obtained from the National Climatic Data Center. Winds for each of 100 sites throughout North America were averaged for the following layers: the surface to 250 meters above ground level (m AGL), 250-500 m AGL, 500-1000 m AGL, 1000-2000 m AGL, and 2000-4000 m AGL. For each of these levels and for each of the 100 meteorological sites, a joint frequency distribution of wind direction (16 cardinal directions) and wind speeds (11 speeds in 1 m/s increments) was calculated for 1990.

These distributions were calculated separately for the twice-daily soundings. The early morning soundings were assumed to be associated with the *E* stability category, and the late afternoon soundings were assumed to be associated with the *C* stability category. Mixing heights were determined from each sounding by calculating the virtual potential temperature. The annual average afternoon mixing heights were calculated for each of the 100 meteorological sites and were used to calculate the upper limit of vertical diffusion (h_m). The appropriate wind layer for concentration calculations was determined using the centroid of the diffusing plume: σ_z for a ground-based plume that has not yet mixed uniformly in the vertical, H for an elevated source, and $h_m/2$ for a uniformly mixed plume (E.H. Pechan & Associates Inc., 1994).

S-R Transfer Coefficients

The S-R matrix used in COBRA estimated the transport of the following emissions species: (1) directly emitted PM_{2.5} and secondary organic aerosols (SOA), (2) sulfur dioxide (SO₂), (3) nitrogen dioxide (NO₂), and (4) ammonia (NH₃). These species were then used in the calculation of ambient concentrations of PM_{2.5}.

A matrix of source-receptor coefficients (in units of s/m³) spanning the entire contiguous U.S. was developed for each of the four pollutants using the CRDM. For a unique combination of source and receptor sites, a S-R transfer coefficient represents the incremental ambient air quality impact in µg/m³ at the receptor resulting from a 1 µg/s unit emission from the source. The S-R matrix therefore provides a link between emission reductions and resulting air quality concentrations. Concentration reductions that occur in proportion to a decrease in emissions at a source are determined by the S-R coefficients for a given source and all receptors.

⁹ Refers to North America wind and temperature. These are standard data tapes for upper-air (rawinsonde) data collected twice daily throughout North America. Rawinsondes are radar-tracked wind balloons.

The pollutant concentration at a destination county is given by:

$$D_j^s = \sum_i \sum_c E_{c,i}^s T_{c,i,j}^s \cdot F^s \cdot F_{unit} \quad (6)$$

where:

- D_j^s = Concentration of pollutant s at destination county j ($\mu\text{g}/\text{m}^3$)
- $E_{i,c}^s$ = Emission of pollutant s from emissions category c in source county i (tons/year)
- $T_{i,j}^s$ = Transfer coefficient for pollutant s from source county i to destination county j for emissions category c (sec/m^3)
- F^s = Ionic conversion factor for pollutant s
- F_{unit} = Unit conversion factor (28,778 $\mu\text{g}\cdot\text{year}/\text{ton}\cdot\text{sec}$)

The ionic conversion factors are molecular weight ratios used to adjust the transfer coefficients to reflect the concentration of precursors to secondarily-formed particulate species. Standard molecular weights along with the ionic conversion factors used in this analysis are given in Exhibit A-4 and Exhibit A-5.

Exhibit A-4. Standard Molecular Weights

Specie	Symbol	Standard molecular weight ¹⁰
Nitrate ion	NO_3^-	62.0049
Sulfate ion	SO_4^{2-}	96.0626
Bisulfate	HSO_4	97.07054
Sulfur Dioxide	SO_2	64.0638
Nitrogen Dioxide	NO_2	46.0055
Ammonia	NH_3	17.03052
Ammonium ion	NH_4^+	18.03846
Ammonium Nitrate	NH_4NO_3	80.04336
Ammonium Bisulfate	NH_4HSO_4	115.109
Ammonium Sulfate	$(\text{NH}_4)_2\text{SO}_4$	132.13952

¹⁰ Standard atomic weights from Coursey, et al. (2011).

Exhibit A-5. Ionic Conversion Factors

Species	Ionic conversion factor, F ^s
PM _{2.5} , SOA	1
SO ₂ → SO ₄ ²⁻	96.0626 / 64.0638
NO ₂ → NO ₃ ⁻	62.0049 / 46.0055
NH ₃ → NH ₄ ⁺	18.03846 / 17.03052

Atmospheric Chemistry

This section describes how secondary reactions are modeled in COBRA, including formation of ammonium bisulfate (NH₄HSO₄), ammonium sulfate ((NH₄)₂SO₄), and ammonium nitrate (NH₄NO₃). Note that the COBRA treats atmospheric chemistry involved in the formation of these pollutants in a more simplified fashion than state-of-the-art air quality models¹¹ (e.g., CALPUFF, AERMOD, CMAQ). We try to address this problem by calibrating COBRA modeling results to measured PM_{2.5} concentrations as described in later in this Appendix. Nevertheless uncertainty remains.

For the atmospheric chemistry in COBRA, in the presence of sulfate (SO₄²⁻) and nitrate (NO₃⁻), ammonium (NH₄⁺) reacts preferentially with SO₄²⁻ to form NH₄HSO₄ and (NH₄)₂SO₄. NH₄NO₃ is only formed under conditions of excess NH₄⁺ and low temperatures. In each destination county, the relative amounts of each secondary particle are subject to the following assumptions:

- SO₄²⁻ is always assumed to be a particle;
- NO₃⁻ is assumed to be a gas, unless it combines with NH₄⁺;
- NH₄⁺ reacts first with SO₄²⁻. The nature of the reaction depends on the relative amounts of NH₄⁺ and SO₄²⁻:
 - If there is a little NH₄⁺, then SO₄²⁻ will be converted to NH₄HSO₄ with potentially some leftover SO₄²⁻;
 - If there is an intermediate amount of NH₄⁺, then a combination of NH₄HSO₄ and (NH₄)₂SO₄ will be obtained;
 - If there is a lot of NH₄⁺, then SO₄²⁻ will be completely converted to (NH₄)₂SO₄;
- After all reactions between NH₄⁺ and SO₄²⁻ occur, any remaining NH₄⁺ reacts with NO₃⁻ to form NH₄NO₃.

Below we lay out the specifics of our approach:

Step 1: Calculate the mole ratio of NH₄⁺ to SO₄²⁻.

$$R = (\text{NH}_4^+ / 18.03846) / (\text{SO}_4^{2-} / 96.0626):$$

¹¹ See U.S. EPA (2012).

a) If $R < 1$ then we assume that a portion of SO_4^{2-} converts to NH_4HSO_4 ($\text{SO}_4^{2-} + \text{NH}_4^+ \rightarrow \text{NH}_4\text{HSO}_4$), while the rest remains as SO_4^{2-}

- Resulting concentration of NH_4HSO_4 is
 $15.109 \cdot \min\{(\text{NH}_4^+ / 18.03846), (\text{SO}_4^{2-} / 96.0626)\}$

- Resulting concentration of remaining SO_4^{2-} is
 $96.0626 \cdot \left((\text{SO}_4^{2-} / 96.0626) - (\text{NH}_4^+ / 18.03846) \right)$

b) If $1 \leq R < 2$ then we assume that all SO_4^{2-} converts to NH_4HSO_4 ($\text{SO}_4^{2-} + \text{NH}_4^+ \rightarrow \text{NH}_4\text{HSO}_4$) and a portion of NH_4HSO_4 converts to $(\text{NH}_4)_2\text{SO}_4$ ($\text{NH}_4\text{HSO}_4 + \text{NH}_4^+ \rightarrow (\text{NH}_4)_2\text{SO}_4$). The second reaction will occur if there is enough NH_4^+ remaining after the first reaction.

- Resulting concentration of NH_4HSO_4 is
 $115.109 \cdot \left(2(\text{SO}_4^{2-} / 96.0626) - (\text{NH}_4^+ / 18.03846) \right)$

- Resulting concentration of $(\text{NH}_4)_2\text{SO}_4$ is
 $132.13952 \cdot \left((\text{NH}_4^+ / 18.03846) - (\text{SO}_4^{2-} / 96.0626) \right)$

c) If $R \geq 2$ then we assume that all SO_4^{2-} converts to $(\text{NH}_4)_2\text{SO}_4$ ($\text{SO}_4^{2-} + 2\text{NH}_4^+ \rightarrow (\text{NH}_4)_2\text{SO}_4$).

- Resulting concentration of $(\text{NH}_4)_2\text{SO}_4$ is
 $132.13952 \cdot (\text{SO}_4^{2-} / 96.0626)$

- Resulting concentration of NH_4^+ (remaining) is
 $18.03846 \cdot \left((\text{NH}_4^+ / 18.03846) - 2(\text{SO}_4^{2-} / 96.0626) \right)$

Step 2: If NH_4^+ remains after Step 1 (c), then NH_4NO_3 formation can take place. The number moles of NO_3^- neutralized in this reaction will be:

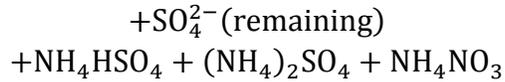
moles of NO_3^- (neutralized) = $\min\{(\text{NH}_4^+ \text{ (remaining)} / 18.03846), (\text{NO}_3^- / 62.0049)\}$.

Step 3: Particulate NH_4NO_3 is stable at relatively low temperatures. Following prior usage of the S-R Matrix (e.g., NO_x SIP Call), we assume that nitrate converts to ammonium nitrate only a quarter of the time (i.e., the winter months). The annual average concentration of NH_4NO_3 formed by the neutralization process is therefore:

$80.04336 \cdot 0.25 \cdot \text{moles of } \text{NO}_3^- \text{ (neutralized)}$.

Step 4: The concentration of $\text{PM}_{2.5}$ at the destination county is estimated as the sum of concentrations of primary $\text{PM}_{2.5}$, SOA, remaining SO_4^{2-} (if any) and secondary NH_4HSO_4 , $(\text{NH}_4)_2\text{SO}_4$, and NH_4NO_3 :

$\text{PM}_{2.5}(\text{total}) = \text{PM}_{2.5}(\text{primary}) + \text{SOA}$



Calibration of S-R Matrix Outputs to Monitoring Data

We calibrated the S-R Matrix model estimates to actual monitoring data obtained from EPA. The county-level calibration factors were estimated using a 2005 emissions inventory developed for the MATS rule and 2005 data from EPA Federal Reference Method (FRM) monitor sites and EPA/National Park Service Visibility Interagency Monitoring of Protected Visual Environments (IMPROVE) program monitor sites.¹²

First, we used the S-R Matrix with the 2005 emissions inventory to estimate PM_{2.5} levels at the center of each county. Second, we spatially interpolated the PM_{2.5} monitor data to generate a monitor-based estimate for each county center as follows:

1. We pre-processed EPA monitoring data to ensure that it did not contain any values flagged as invalid and that minimum number of daily measurements per quarter was 11;¹³
2. We calculated quarterly average PM_{2.5} concentrations for all monitoring sites with sufficient data;
3. For each quarter, we used an automatic kriging routine from R project package ‘automap’ (Hiemstra, 2012) to interpolate quarterly average PM_{2.5} values to county centroids;
4. At each county centroid we then average over the interpolated quarterly average PM_{2.5} values to generate an annual average PM_{2.5} value.

We calculated a “calibration factor” for each county by dividing our monitor estimate by the model estimate. These county-level calibration factors ranged from 0.35 to 3.02 with a mean value of 1.25. For each state, Exhibit A-6 gives the average of the county-level monitor and model values as well as the ratio of the two (the ratio being the average of the calibration factors).

When calculating future year PM_{2.5} levels in COBRA, we use the calibration factors to adjust our model estimate for each county in the following way:

$$PM_{2.5}(\text{calibrated model, 2017}) \\ = PM_{2.5}(\text{model, 2017}) \cdot \left(\frac{PM_{2.5}(\text{interpolated monitor, 2005})}{PM_{2.5}(\text{model, 2005})} \right)$$

To sum up, the steps involved in the calculation of 2017 ambient PM_{2.5} levels in COBRA are the following. We start the process by running the CRDM model, which generates the S-R Matrix transfer coefficients. Emissions data for 2005 are run through the S-R Matrix and atmospheric

¹² These data are available with the distribution of EPA’s Modeled Attainment Test Software (U.S. EPA, 2010b).

¹³ The choice of 11 as the minimum number of site-days per valid quarter corresponds to > 75% completeness for monitors on a 1 in 6 day schedule. This is a minimum number of samples that is routinely used in calculations of quarterly average concentrations by EPA.

chemistry calculations applied to generate un-calibrated 2005 model estimates. Monitoring data for 2005 were interpolated to the county-level, and were then compared with the 2005 model estimates to generate calibration factors. Estimates of 2017 ambient PM_{2.5} levels can then be generated by running the 2017 emissions data through the S-R Matrix. The resulting 2017 model PM_{2.5} levels are then multiplied with the previously generated county-level calibration factors to calculate a best estimate of 2017 calibrated ambient PM_{2.5} levels.

Exhibit A-6. Monitor and Model Average PM_{2.5} Levels (ug/m3) in 2005 and Average of Monitor to Model Ratios by State

State	Monitor	Model	Ratio	State	Monitor	Model	Ratio
AL	13.91	12.70	1.10	MT	5.13	3.33	1.55
AR	13.68	10.59	1.30	NC	13.63	12.85	1.08
AZ	6.13	5.16	1.26	ND	5.02	3.83	1.31
CA	7.86	7.79	1.15	NE	8.30	5.77	1.45
CO	5.25	5.62	0.97	NH	9.25	9.31	1.02
CT	11.50	12.35	0.93	NJ	13.27	15.95	0.85
DC	14.57	22.79	0.64	NM	5.36	5.44	1.01
DE	13.89	14.96	0.94	NV	6.60	4.57	1.58
FL	10.45	10.86	1.00	NY	11.89	11.35	1.13
GA	13.18	14.41	0.94	OH	15.98	14.03	1.15
IA	11.90	7.24	1.66	OK	10.29	8.68	1.21
ID	6.27	5.58	1.20	OR	5.93	4.72	1.45
IL	15.11	10.90	1.40	PA	14.41	13.53	1.10
IN	16.02	14.09	1.15	RI	10.77	10.35	1.05
KS	9.27	7.48	1.29	SC	13.06	12.87	1.02
KY	15.94	12.99	1.24	SD	7.09	4.49	1.58
LA	12.98	9.94	1.36	TN	15.21	12.48	1.22
MA	10.39	12.21	0.90	TX	9.87	6.99	1.50
MD	14.40	16.69	0.89	UT	5.40	5.52	1.01
ME	7.46	6.46	1.22	VA	14.50	14.15	1.04
MI	11.83	8.90	1.36	VT	9.04	7.98	1.13
MN	8.18	7.49	1.16	WA	5.74	3.81	1.65
MO	13.58	9.83	1.41	WI	10.92	8.08	1.37
MS	13.96	11.58	1.21	WV	15.73	12.83	1.24
				WY	5.36	4.33	1.26

Appendix B: Derivation of Health Impact Functions

This appendix reviews the steps we performed in taking models from the epidemiological study and converting them into health impact functions, which we then use to quantify the change in adverse health effects due to a change in air pollution exposure. The most common functional forms are the log-linear and logistic, with a linear model used in some cases. All three are discussed below.

Note that the log-linear and logistic generally produce comparable results, so the fact that some health impacts are estimated with a logistic function and others with a log-linear function is not a cause for concern. Indeed, in some circumstances, such as for small changes in air pollution, the logistic and log-linear produce essentially the same result.

The Linear Model

A linear model between the adverse health effect, y , and the pollutant concentration, x , is of the form

$$y = \alpha + \beta \cdot x$$

A linear model includes the factors that are believed to affect the incidence of the health effect, of which the pollutant would be one. So, the variable “ α ” in the linear function consists of all the other independent variables in the regression, typically evaluated at their mean values, times their respective coefficients.

The function describing the relationship between a change in x and the corresponding change in incidence (rate) of the health effect from the baseline level (y_b) to the post-control level (y_c) is then:

$$\Delta y = y_b - y_c = \beta \cdot (x_b - x_c) = \beta \cdot \Delta x$$

If y denotes an incidence rate, then Δy denotes the change in the incidence rate. If y denotes an incidence count, then the β is first divided by the baseline study population to generate an incidence rate. Δx is the difference between the baseline level of the pollutant concentration and the control level of the pollutant concentration: $x_b - x_c$. (Note that typically a control strategy is intended to decrease the pollutant levels, so we expect Δx to be positive.) The expected number of cases avoided would then be calculated by multiplying Δy by the relevant population:

$$\text{CasesAvoided} = \beta \cdot \Delta x \cdot \text{population}$$

The coefficient, β , and standard error of β (σ_β) are reported directly in studies presenting results from linear regression models.

The Log-linear Model

The most commonly used functional form for criteria air pollutant concentration-response functions is the log-linear model. It defines the relationship between x and y to be of the form:

$$y = B \cdot \exp(\beta \cdot x)$$

or, equivalently,

$$\ln(y) = \alpha + \beta \cdot x,$$

where the parameter B is the incidence (rate) corresponding to the zero pollutant concentration ($x = 0$); the coefficient β is the effect of pollutant x on the natural logarithm of the incidence (rate) $y - \ln(y)$; and $\alpha = \ln(B)$.¹

Estimating Avoided Cases

The relationship between Δx and Δy is:

$$\Delta y = y_b - y_c = B(\exp(\beta x_b) - \exp(\beta x_c))$$

This may be rewritten as:

$$\Delta y = y_b \cdot \left(1 - \frac{1}{\exp(\beta \cdot \Delta x)}\right)$$

where y_b is the baseline incidence (rate) of the health effect – i.e., the incidence (rate) before the change in x . If y is incidence rate rather than incidence count, then the change in incidence rate, Δy , must be multiplied by the relevant population to get the expected number of cases avoided. For example, if y denotes the annual number of cases of the adverse health effect per 100,000 population then the expected number of cases avoided is calculated as:

$$CasesAvoided = \frac{y_b}{100,000} \cdot population \cdot \left(1 - \frac{1}{\exp(\beta \cdot \Delta x)}\right)$$

Estimating the Coefficient (β)

Epidemiological studies that estimate log-linear concentration-response functions often report a relative risk for a specific Δx , rather than the coefficient, β , in the function itself. The relative risk (RR) is simply the ratio of two risks corresponding to two levels of pollutant concentration – the “high” risk y_{high} (corresponding to the higher pollutant level, $x = x_{high}$) and the lower risk y_{low} (corresponding to the lower pollutant level, $x = x_{low}$):

$$RR = \frac{y_{high}}{y_{low}}$$

¹ Other covariates besides pollution clearly affect mortality. The parameter B might be thought of as containing these other covariates, for example, evaluated at their means. That is, $B = B_0 \exp\{\beta_1 x_1 + \dots + \beta_n x_n\}$, where B_0 is the incidence of y when all covariates in the model are zero, and x_1, \dots, x_n are the other covariates evaluated at their mean values. The parameter B drops out of the model, however, when changes in y are calculated, and is therefore not important.

Using the original log-linear function above, it can be shown that the relative risk associated with a specific change in pollutant concentration of $\Delta x^* = x_{high} - x_{low}$ can be written as

$$RR|_{\Delta x^*} = \frac{y_{high}}{y_{low}} = \exp(\beta \cdot \Delta x^*)$$

Taking the natural log of both sides, the coefficient in the function underlying the relative risk can be derived as:

$$\beta = \frac{\ln(RR)}{\Delta x^*}$$

Once the pollutant coefficient, β , has been calculated, the change in incidence (rate), Δy , corresponding to any change in pollutant concentration, Δx , can be calculated, using the relationship between Δx and Δy given above, the baseline incidence (rate) and assessment population.

There are instances when epidemiological studies report percent increase in the relative risk, rather than relative risk itself. Given a reported x percent increase in the relative risk, we back-calculate the relative risk as $RR = 1 + x/100$. Then we proceed to calculating β as described above. Note that some epidemiological studies (see, e.g., Moolgavkar [2003]) further define x to be $\log(RR) \times 100$. In these cases, our approach to computing the RR is an approximation, although the error introduced is small. This approximation is consistent with EPA's PM_{2.5} health benefits model implemented in EPA's BenMAP-CE.

Estimating the Standard Error of β (σ_β)

The standard error of β (σ_β) is not often directly reported in studies presenting results from log-linear regression models. Results are most commonly presented as a relative risk and 95% confidence interval. The 95% confidence interval is defined as follows:

$$CI_{95\%} = \exp(\beta \cdot \Delta x \pm 1.96 \cdot \sigma_\beta \Delta x)$$

Based on this equation, the standard error of β (σ_β) can be estimated from the relative risk (RR), upper limit of the 95% confidence interval (UL), and lower limit of the 95% confidence interval (LL), as follows:

$$\sigma_{\beta,high} = \frac{\beta_{high} - \beta}{1.96} = \frac{(\ln(UL)/\Delta x - \ln(RR)/\Delta x)}{1.96} \quad \text{and} \quad \sigma_{\beta,low} = \frac{\beta - \beta_{low}}{1.96} = \frac{(\ln(RR)/\Delta x - \ln(LL)/\Delta x)}{1.96}$$

$$\sigma_\beta \cong \frac{\sigma_{\beta,high} + \sigma_{\beta,low}}{2} \quad \text{or} \quad \sigma_\beta \cong \frac{\beta_{high} - \beta_{low}}{3.92}$$

Some studies report only a central effect estimate and t -statistic. The t -statistic describes the strength of the observed pollutant-health effect association. It is defined as the ratio of the

coefficient, β , to the standard error of β (σ_β). The standard error of β (σ_β) can, therefore, be estimated from the t -statistic as follows:

$$\sigma_\beta = \frac{\beta}{t}$$

The Logistic Model

In some epidemiological studies, a logistic model is used to estimate the probability of an occurrence of an adverse health effect. Given a pollutant level, x , and a vector of other explanatory variables, Z , the logistic model assumes the probability of an occurrence is:

$$y = P(\text{occurrence} | \beta \cdot x, \alpha \cdot Z) = \frac{\exp(\beta \cdot x) \exp(\alpha \cdot Z)}{1 + \exp(\beta \cdot x) \exp(\alpha \cdot Z)},$$

where β is the coefficient of the pollutant concentration, x , and α is a vector of coefficients of the variables in the vector Z .²

Estimating Avoided Cases

The change in the probability of an occurrence (Δy) corresponding to a change in the level of the pollutant from x_b to x_c ($= \Delta x$), all other covariates held constant, may be derived from the original C-R function above:

$$\Delta y = y_b - y_c = y_b \left(1 - \frac{1}{(1 - y_b) \cdot \exp(\beta \cdot \Delta x) + y_b} \right)$$

Once again, to calculate the expected number of avoided cases of the adverse effect, it is necessary to multiply by the population:³

$$\text{Cases Avoided} = y_b \left(1 - \frac{1}{(1 - y_b) \cdot \exp(\beta \cdot \Delta x) + y_b} \right) \cdot \text{population}$$

Estimating the Coefficient (β)

The estimated pollutant coefficient, β , in the original function is typically not reported in studies that use the logistic model. Instead, the odds ratio (OR) corresponding to a specific change in x is reported.

The odds of an occurrence is defined as:

$$\text{Odds} = \frac{y}{1 - y}$$

It can be shown that:

$$\text{Odds} = \frac{y}{1 - y} = \exp(\beta \cdot x) \exp(\alpha \cdot Z)$$

² Greene (1997, Chapter 19) presents models with discrete dependent variables; in particular, page 874 presents the logit model. See also Judge et al. (1985, p. 763).

³ Note that because Δy here is a change in probability of occurrence (rather than a change in the rate per 100,000 population), it is necessary to multiply by the population rather than by the population/100,000.

The odds ratio is just the ratio of the odds when the pollutant is at a specified higher level, x_{high} , to the odds when the pollutant is at a specified lower level, x_{low} :

$$OR = \frac{\exp(\beta \cdot x_{high}) \exp(\alpha \cdot Z)}{\exp(\beta \cdot x_{low}) \exp(\alpha \cdot Z)} = \frac{\exp(\beta \cdot x_{high})}{\exp(\beta \cdot x_{low})} = \exp(\beta \cdot \Delta x)$$

Often the odds ratio corresponding to a specified change in x , call it Δx^* , is the only measure of the effect of x reported from a study using a logistic model (just as the relative risk corresponding to a specified change in x is often the only measure of the effect of x reported from a study using a log-linear model). However, it is easy to calculate the underlying pollutant coefficient, β , from the odds ratio as follows:

$$OR|_{\Delta x^*} = \exp(\beta \cdot \Delta x^*) \rightarrow \ln(OR) = \beta \cdot \Delta x^* \rightarrow \beta = \frac{\ln(OR)}{\Delta x^*}$$

Given the pollutant coefficient, β , and the baseline probability of occurrence, y_b , the change in the probability, Δy , associated with any change in pollutant concentration, Δx , can be derived using the equation for Δy above. The expected number of avoided cases of the adverse effect is then obtained by multiplying by the population.

Estimating the Standard Error of β (σ_β)

The standard error of β (σ_β) is not often directly reported in studies presenting results from logistic regression models. Results are most commonly presented as an odds ratio and 95% confidence interval. The 95% confidence interval is defined as follows:

$$CI_{95\%} = \exp(\beta \cdot \Delta x \pm 1.96 \cdot \sigma_\beta \Delta x)$$

Based on this equation, the standard error of β (σ_β) can be estimated from the odds ratio (OR), upper limit of the 95% confidence interval (UL), and lower limit of the 95% confidence interval (LL), as follows:

$$\sigma_{\beta,high} = \frac{\beta_{high} - \beta}{1.96} = \frac{(\ln(UL)/\Delta x - \ln(OR)/\Delta x)}{1.96} \quad \text{and} \quad \sigma_{\beta,low} = \frac{\beta - \beta_{low}}{1.96} = \frac{(\ln(OR)/\Delta x - \ln(LL)/\Delta x)}{1.96}$$

$$\sigma_\beta \cong \frac{\sigma_{\beta,high} + \sigma_{\beta,low}}{2} \quad \text{or} \quad \sigma_\beta \cong \frac{\beta_{high} - \beta_{low}}{3.92}$$

Some studies report only a central effect estimate and t -statistic. The t -statistic describes the strength of the observed pollutant-health effect association. It is defined as the ratio of the coefficient, β , to the standard error of β (σ_β). The standard error of β (σ_β) can, therefore, be estimated from the t -statistic as follows:

$$\sigma_\beta = \frac{\beta}{t}$$

Appendix C: Health Impact Functions

A reduction in ambient PM_{2.5} levels is associated with reductions in a number of adverse health effects, or “endpoints.” This appendix discusses the calculation of avoided adverse health effects. The health impact functions in the COBRA model were prepared by Abt Associates in close consultation with EPA and rely on an up-to-date assessment of the published scientific literature to ascertain the relationship between particulate matter and adverse human health effects. We evaluated studies using a variety of selection criteria, including: study location and design, the characteristics of the study population, and whether the study was peer-reviewed (Exhibit C-1).

Exhibit C-1. Summary of Considerations Used in Selecting Studies

Consideration	Comments
Peer reviewed research	Peer reviewed research is preferred to research that has not undergone the peer review process.
Study type	Among studies that consider chronic exposure (e.g., over a year or longer) prospective cohort studies are preferred over cross-sectional studies because they control for important individual-level confounding variables that cannot be controlled for in cross-sectional studies.
Study period	Studies examining a relatively longer period of time (and therefore having more data) are preferred, because they have greater statistical power to detect effects. More recent studies are also preferred because of possible changes in pollution mixes, medical care, and life style over time.
Study size	Studies examining a relatively large sample are preferred because they generally have more statistical power to detect small magnitude effects. A large sample can be obtained in several ways, either through a large population, or through repeated observations on a smaller population, e.g. through a symptom diary recorded for a panel of asthmatic children.
Study location	U.S. studies are more desirable than non-U.S. studies because of potential differences in pollution characteristics, exposure patterns, medical care system, population behavior and life style.
Measure of PM	For this analysis, C-R functions based on PM _{2.5} are preferred to those based on PM ₁₀ (particulate matter less than 10 microns in aerodynamic diameter) because reductions in emissions from diesel engines are expected to reduce fine particles and not have much impact on coarse particles.
Economically valuable health effects	Some health effects, such as changes in forced expiratory volume and other technical measurements of lung function, are difficult to value in monetary terms. These health effects are therefore not quantified in this analysis.
Non-overlapping endpoints	Although the benefits associated with each individual health endpoint may be analyzed separately, care must be exercised in selecting health endpoints to include in the overall benefits analysis because of the possibility of double counting of benefits. Including emergency room visits in a benefits analysis that already considers hospital admissions, for example, will result in double counting of some benefits if the category "hospital admissions" includes emergency room visits.

Model Selection

In many epidemiological studies of air pollution and health, researchers estimate and present numerous single pollutant and multi-pollutant models for the same pollutant and health endpoint. These models may differ from each other in a number of characteristics, including: the functional

form of the model, the covariates included in the model, the pollutant exposure metric, the lag structure, and the study population.

For the purposes of estimating health benefits associated with pollutant changes, it is neither realistic nor advantageous to include every model presented in each study. However, it is important that a relatively objective process be used to select from among models. Described below are the criteria that were used as guidance in the selection of a particular model from among several models presented in a study. It is not possible in all cases to select a model using a completely objective and mechanical process. In many cases, professional judgment and an understanding of the study context are necessary as well to select the most appropriate models. Exhibit C-2 summarizes the selection criteria that we used.

Exhibit C-2. Description of Selection Criteria

Selection Criteria	Description
Goodness-of-fit statistics	If an appropriate measure of goodness of fit (i.e., how well the model fit the data) is reported for each of several models in a study, then this measure may be used as the basis on which to select a model.
Best captures distributed lag	Select the model that appears to best capture a distributed lag effect, as described below. If multiple single-lag models and/or moving average models are specified, select the model with the largest effect estimate, all else equal.
Best set of control variables	Select the model which includes temporal variables (i.e. season, weather patterns, day of the week) and other known non-pollutant confounders, all else equal. Select the model which uses the most sophisticated methods of capturing the relationship between these variables and the dependent variable (e.g., affords the most flexibility in fitting possible nonlinear trends).
Useful for health effects modeling	The model must be in a form that is useful for health effects modeling (e.g., the pollutant variable should be a continuous variable rather than a categorical variable).
Sample size	Select the model estimated with the larger sample size, all else equal.

Distributed Lag Effect

The question of lags and the problems of correctly specifying the lag structure in a model has been discussed extensively (U.S. EPA, 2002, Section 8.4.4). In many time-series studies, after the basic model is fit (before considering the pollutant of interest), several different lags are typically fit in separate single-lag models and the most significant lag is chosen. The 2002 draft PM_{2.5} CD notes that “while this practice may bias the chance of finding a significant association, without a firm biological reason to establish a fixed pre-determined lag, it appears reasonable” (U.S. EPA, 2002, p. 8-237).

There is recent evidence (Schwartz, 2000) that the relationship between PM_{2.5} and health effects may best be described by a distributed lag (i.e., the incidence of the health effect on day n is influenced by PM_{2.5} concentrations on day n, day n-1, day n-2 and so on). If this is the case, a model that includes only a single lag (e.g., a 0-day lag or a 1-day lag) is likely to understate the total impact of PM_{2.5}. The 2002 draft PM_{2.5} CD makes this point, noting that “if one chooses the

most significant single lag day only, and if more than one lag day shows positive (significant or otherwise) associations with mortality, then reporting a RR [relative risk] for only one lag would also underestimate the pollution effects” (U.S. EPA, 2002, p. 8-241). The same may hold true for other pollutants that have been associated with various health effects.

Several studies report similar models with different lag structures. For example, Moolgavkar (2000a) studied the relationship between air pollution and respiratory hospital admissions in three U.S. metropolitan areas. The author reports models with PM_{2.5} lagged from zero to five days. Since the lagging of PM_{2.5} was the only difference in the models and the relationship is probably best described using a distributed lag model, any of single-lag effect estimates are likely to underestimate the full effect. Therefore, we selected the model with the largest effect estimate.

Pooling

There is often more than one study that has estimated a health impact function for a given pollutant-health endpoint combination. Each study provides an estimate of the pollutant coefficient, β , along with a measure of the uncertainty of the estimate. Because uncertainty decreases as sample size increases, combining data sets is expected to yield more reliable estimates of β , and therefore more reliable estimates of the incidence change predicted using β . Combining data from several comparable studies in order to analyze them together is often referred to as meta-analysis.

For a number of reasons, including data confidentiality, it is often impractical or impossible to combine the original data sets. Combining the results of studies in order to produce better estimates of β provides a second-best but still valuable way to synthesize information. This is referred to as pooling. Pooling β 's requires that all of the studies contributing estimates of β use the same functional form for the health impact function. That is, the β 's must be measuring the same thing.

To be consistent with the recent EPA benefits analyses, COBRA uses a random-/ fixed- effects pooling procedure (see U.S. EPA, 2009, p. 5-18), which is a method for weighting estimates involving using their variances. Variance takes into account both the consistency of data and the sample size used to obtain the estimate, two key factors that influence the reliability of results. The method is based on DerSimonian and Laird (1986).

Fixed Effect Weights

The fixed effects model assumes that there is a single true concentration-response relationship and therefore a single true value for the parameter β that applies everywhere. Differences among β 's reported by different studies are therefore simply the result of sampling error. That is, each reported β is an estimate of the same underlying parameter. The certainty of an estimate is reflected in its variance (the larger the variance, the less certain the estimate). Fixed effects pooling therefore weights each estimate under consideration in proportion to the inverse of its variance:

$$\beta_{fe} = \frac{\sum_{n=1}^N \frac{\beta_n}{v_n}}{\sum_{n=1}^N \frac{1}{v_n}}$$

Where

N – number of studies;

β_n – estimate provided by study n ;

v_n – variance of the estimate provided by study n ;

β_{fe} – pooled fixed effects estimate.

Random- / Fixed- Effect Weights

An alternative to the fixed effects model is the random effects model, which allows the possibility that the estimates β_n from the different studies may in fact be estimates of different parameters, rather than just different estimates of a single underlying parameter. In studies of the effects of PM_{2.5} on hospitalizations for COPD, for example, if the composition of PM_{2.5} varies among study locations the underlying relationship between the frequency of hospitalizations for COPD and PM_{2.5} may be different from one study location to another. This would violate the assumption of the fixed effects model.

It is possible to test whether it is appropriate to base the pooling on the random effects model (vs. the fixed effects model). A test statistic, Q_w , the weighted sum of squared differences of the separate study estimates from the pooled estimate based on the fixed effects model β_{fe} , is calculated as:

$$Q_w = \sum_{n=1}^N \frac{(\beta_n - \beta_{fe})^2}{v_n}$$

Under the null hypothesis that there is a single underlying parameter, β , of which all the β_n 's are estimates, Q_w has a chi-squared distribution with $N-1$ degrees of freedom. (Recall that N is the number of studies in the meta-analysis.) If Q_w is greater than the critical value corresponding to the desired confidence level, the null hypothesis is rejected. That is, in this case the evidence does not support the fixed effects model, and the random effects model is assumed, allowing the possibility that each study is estimating a different β . We use a five percent one-tailed test.

The random effect model-based pooling must take into account not only the within-study variances (used in a meta-analysis based on the fixed effects model) but the between-study variance as well. The between-study variance, η^2 , is given by:

$$\eta^2 = \frac{Q_w - (N - 1)}{\sum_{n=1}^N 1/v_n - \frac{\sum_{n=1}^N 1/v_n^2}{\sum_{n=1}^N 1/v_n}}$$

(i.e., if $Q_w < N-1$), then η^2 is a negative number, and it is not possible to calculate a random effects estimate. In this case, however, the small value of Q_w would presumably have led to accepting the null hypothesis described above, and the meta-analysis would be based on the fixed effects model. The remaining discussion therefore assumes that η^2 is positive.

Given a value for η^2 , the random effects estimate is calculated in almost the same way as the fixed effects estimate. However, the pooled estimate now incorporates both the within-study variance (v_n) and the between-study variance (η^2):

$$\beta_{re} = \frac{\sum_{n=1}^N \beta_n}{\sum_{n=1}^N \frac{1}{\eta^2 + v_n}}$$

Where

N – number of studies;

β_n – estimate provided by study n ;

v_n – variance of the estimate provided by study n ;

η^2 – within-study variance;

β_{re} – pooled random effects estimate.

The weighting scheme used in a pooling based on the random effects model is basically the same as that used if a fixed effects model is assumed, but the variances used in the calculations are different. This is because a fixed effects model assumes that the variability among the estimates from different studies is due only to sampling error (i.e., each study is thought of as representing just another sample from the same underlying population), while the random effects model assumes that there is not only sampling error associated with each study, but that there is also between-study variability – each study is estimating a different underlying β . Therefore, the sum of the within-study variance and the between-study variance yields an overall variance estimate.

Thresholds

Health impact functions have been developed with and without explicit thresholds. A threshold means that air pollution levels below the specified threshold have no adverse health effects. In some prior regulatory impact assessments (e.g., U.S. EPA, 2006) assumed a threshold of $10 \mu\text{g}/\text{m}^3$ for $\text{PM}_{2.5}$. However, EPA's most current understanding of the scientific literature is that there is no threshold in the relationship between $\text{PM}_{2.5}$ and adverse health impacts. In its recent analysis of proposed NO_2 national ambient air quality standards, U.S. EPA (2009) used a no-threshold model to calculate $\text{PM}_{2.5}$ co-benefits down to the lowest modeled $\text{PM}_{2.5}$ air quality levels.

Following EPA's updated methodology, we also assume there is no threshold for modeling $\text{PM}_{2.5}$ -related health effects. This is supported by the National Research Council (2002) in its review of methods for estimating the public health benefits of air pollution regulations. They concluded that there is no evidence for any departure from linearity in the observed range of

exposure to PM₁₀ or PM_{2.5}, nor is there any indication of a threshold. They cite the weight of evidence available from both short- and long-term exposure models and the similar effects found in cities with low and high ambient concentrations of PM_{2.5}. More recently, Schwartz et al (2008) reached the same conclusion, finding a linear relationship between PM_{2.5} and premature mortality with no evidence of a threshold.

In addition, U.S. EPA completed an “expert elicitation” analysis in which it elicited opinions from 12 experts (in epidemiology, toxicology, and medicine) on the nature of this relationship (see: Industrial Economics Incorporated (IEc), 2006). The experts were asked how likely they thought it is that the relationship between PM_{2.5} and mortality is causal, and if it is causal, what is the functional form of the C-R relationship, including whether there is a threshold. Eleven of the twelve experts thought that, although each individual may have a threshold, there is insufficient empirical evidence for a threshold for the population, which is the entity of interest in a C-R function. Only one expert did include the possibility of a population threshold, assigning a probability of 50 percent to there being a threshold and, if there is a threshold, an 80 percent chance that it is less than or equal to 5 µg/m³ (which is below the level of PM_{2.5} observed in epidemiological studies), and a 20 percent chance that it is between 5 and 10 µg/m³.

Summary of Health Impact Functions Used in COBRA

In this Appendix, we present the health impact functions used to estimate PM_{2.5}-related adverse health effects. Exhibit C-3 summarizes the epidemiological studies in COBRA used to estimate adverse health impacts of PM_{2.5}. Each sub-section has an exhibit with a brief description of the health impact function and the underlying parameters. Following each exhibit, we present a brief summary of each study and any information that is unique to that study.

Exhibit C-3. Epidemiological Studies Used to Estimate Adverse Health Impacts of PM_{2.5}

Endpoint	Author	Age
Mortality, All Cause	Krewski et al. (2009)	30-99
Mortality, All Cause	Lepeule et al. (2012)	25-99
Mortality, All Cause	Woodruff et al. (1997)	Infant
Acute Myocardial Infarction, Nonfatal	Peters et al. (2001)	18-99
Acute Myocardial Infarction, Nonfatal	Pope et al. (2006)	18-99
Acute Myocardial Infarction, Nonfatal	Sullivan et al. (2005)	18-99
Acute Myocardial Infarction, Nonfatal	Zanobetti and Schwartz (2006)	18-99
Acute Myocardial Infarction, Nonfatal	Zanobetti et al. (2009)	18-99
HA, All Cardiovascular (less Myocardial Infarctions)	Bell et al. (2008)	65-99
HA, All Cardiovascular (less Myocardial Infarctions)	Moolgavkar (2000b)	18-64
HA, All Cardiovascular (less Myocardial Infarctions)	Peng et al. (2008)	65-99
HA, All Cardiovascular (less Myocardial Infarctions)	Peng et al. (2009)	65-99
HA, All Cardiovascular (less Myocardial Infarctions)	Zanobetti et al. (2009)	65-99
HA, All Respiratory	Zanobetti et al. (2009)	65-99
HA, All Respiratory	Kloog et al. (2012)	65-99
HA, Asthma	Babin et al. (2007)	0-17
HA, Asthma	Sheppard (2003)	0-17
HA, Chronic Lung Disease	Moolgavkar (2000a)	18-64
Emergency Room Visits, Asthma	Mar et al. (2010)	0-99
Emergency Room Visits, Asthma	Slaughter et al. (2005)	0-99
Emergency Room Visits, Asthma	Glad et al. (2012)	0-99
Acute Bronchitis	Dockery et al. (1996)	8-12
Asthma Exacerbation, Cough	Mar et al. (2004)	6-18
Asthma Exacerbation, Cough	Ostro et al. (2001)	6-18
Asthma Exacerbation, Shortness of Breath	Mar et al. (2004)	6-18
Asthma Exacerbation, Shortness of Breath	Ostro et al. (2001)	6-18
Asthma Exacerbation, Wheeze	Ostro et al. (2001)	6-18
Minor Restricted Activity Days	Ostro and Rothschild (1989)	18-64
Lower Respiratory Symptoms	Schwartz and Neas (2000)	7-14
Upper Respiratory Symptoms	Pope et al. (1991)	9-11
Work Loss Days	Ostro (1987)	18-64

Note that Appendix B mathematically derives the standard types of health impact functions that we encountered in the epidemiological literature, such as, log-linear, logistic and linear, so we simply note here the type of functional form. Appendix D presents a description of the sources for the incidence and prevalence data used in these health impact functions.

Mortality

Health researchers have consistently linked air pollution, especially PM_{2.5}, with excess mortality. Although a number of uncertainties remain to be addressed, a substantial body of published scientific literature recognizes a correlation between elevated PM_{2.5} concentrations and increased mortality rates. Based on the scientific evidence, EPA’s Integrated Science Assessment determined a causal relationship between PM_{2.5} and premature mortality (<http://www.epa.gov/ncea/isa/>).

Both long- and short-term exposures to ambient levels of particulate matter air pollution have been associated with increased risk of premature mortality. It is clearly an important health endpoint because of the size of the mortality risk estimates, the serious nature of the effect itself, and the high monetary value ascribed to avoiding mortality risk. Because of the importance of this endpoint and the considerable uncertainty among economists and policymakers as to the appropriate way to estimate PM-related mortality risks, this section discusses some of the issues surrounding the estimation of premature mortality associated with PM_{2.5}.

Particulate matter has been linked with premature mortality in adults in multiple studies throughout the world (Jerrett et al., 2005; Katsouyanni et al., 2001; Laden et al., 2006; Pope et al., 2002; Samet, Dominici, Curriero, Coursac, & Zeger, 2000) as well as infants (Bobak & Leon, 1999; Conceicao, Miraglia, Kishi, Saldiva, & Singer, 2001; Loomis, Castillejos, Gold, McDonnell, & Borja-Aburto, 1999; Woodruff, Darrow, & Parker, 2008; Woodruff et al., 1997). To estimate premature mortality in adults, we use an epidemiological analysis of the American Cancer Society cohort by Krewski et al. (2009) and analysis of the Six-City cohort by Lepeule et al. (2012). To estimate premature mortality in infants, we used a study by Woodruff et al. (1997).

Exhibit C-4. Health Impact Functions for Particulate Matter and All-Cause Mortality

Author	Year	Location	Age	Metric	Beta	Std Err	Functional Form
Krewski et al.	2009	116 U.S. cities	30-99	Annual	0.005827	0.000963	Log-linear
Lepeule et al.	2012	6 Eastern cities	25-99	Annual	0.013103	0.003347	Log-linear
Woodruff et al.	1997	86 cities	0-0	Annual	0.003922	0.001221	Logistic

Note that COBRA does not pool Krewski et al. (2009) and Lepeule et al. (2012) to estimate premature mortality in adults. In recent analysis of proposed NO₂ national ambient air quality standards, U.S. EPA (2009) used Pope et al. (2002)¹ and Laden et al. (2006) to estimate the PM_{2.5} mortality-related co-benefits and presented the results separately for each study:

“These are logical choices for anchor points in our presentation because, while both studies are well designed and peer reviewed, there are strengths and weaknesses inherent

¹ Krewski et al. (2009) is an extended and updated analysis of Pope et al. (2002).

in each, which we believe argues for using both studies to generate benefits estimates. Previously, EPA had calculated benefits based on these two empirical studies, but derived the range of benefits, including the minimum and maximum results, from an expert elicitation of the relationship between exposure to PM_{2.5} and premature mortality (Roman et al., 2008). Within this assessment, we include the benefits estimates derived from the concentration-response function provided by each of the twelve experts to better characterize the uncertainty in the concentration-response function for mortality and the degree of variability in the expert responses. Because the experts used these cohort studies to inform their concentration-response functions, benefits estimates using these functions generally fall between results using these epidemiology studies (see Figure 5.9). In general, the expert elicitation results support the conclusion that the benefits of PM_{2.5} control are very likely to be substantial.” p. 5-25.

Mortality, All Cause (Krewski et al., 2009)

This cohort study consists of approximately 360,000 participants residing in areas of the country that have adequate monitoring information on levels of PM_{2.5} for 1980 and about 500,000 participants in areas with adequate information for 2000. The causes of death that were analyzed included all causes, cardiopulmonary disease (CPD), ischemic heart disease (IHD), lung cancer, and all remaining causes. Data for 44 personal, individual-level covariates, based on participants' answers to a 1982 enrollment questionnaire, were also used for the analyses. The authors also collected data for seven ecologic (neighborhood-level) covariates, each of which represents local factors known or suspected to influence mortality, such as poverty level, level of education, and unemployment (at both zip code and city levels). Long-term average exposure variables were constructed for PM_{2.5} from monitoring data for two periods: 1979-1983 and 1999-2000. Similar variables were constructed for long-term exposure to other pollutants of interest from single-year (1980) averages, including total suspended particles, ozone, nitrogen dioxide, and sulfur dioxide. Exposure was averaged for all monitors within a metropolitan statistical area (MSA) and assigned to participants according to their Zip Code area (ZCA) of residence.

The authors chose the standard Cox proportional-hazards model (and a variation to allow for random effects) to calculate hazard ratios for various cause-of-death categories associated with the levels of air pollution exposure in the cohort. They extended the random effects Cox model to accommodate two levels of information for clustering and for ecologic covariates. Three main analyses were conducted: a Nationwide Analysis, Intra-Urban Analyses in the New York City (NYC) and Los Angeles (LA) regions, and an analysis designed to investigate whether critical time windows of exposure to pollutants might have affected mortality in the cohort. Using a multi-pollutant model (O₃, SO₄, SO₂, TSP, and PM_{2.5}), the authors reported a relative risk (1.06) for all-cause mortality and the corresponding 95% confidence interval (95% CI: 1.04-1.08) for a 10 µg/m³ increase in the average of PM_{2.5} exposure level for 1999-2000 (Krewski et al., 2009, Commentary Table 4). The results were adjusted for the 44 individual-level covariates and the 7 ecologic covariates at the MSA & DIFF levels.

Functional Form: Log-linear

Coefficient: 0.005827

Standard Error: 0.000963

Incidence Rate: county-specific annual all-cause mortality rate per person ages 30 and older

Population: population of ages 30 and older

Mortality, All Cause (Lepeule et al., 2012)

Lepeule et al. (2012) is an extended and updated analysis of Laden et al. (2006). The authors performed an extended mortality follow-up from 1979-2009 using data from the Harvard Six Cities adult cohort study. They used annual city-specific PM_{2.5} concentrations and assigned for each participant until death or censoring. The authors replicated the previously applied Cox regression (as used in Laden et al., 2006), and examined different time lags, the shape of the concentration–response relationship using penalized splines, and changes in the slope of the relation over time. Then they conducted Poisson survival analysis with time-varying effects for smoking, sex, and education. The authors found a significant increase in the overall mean mortality associated with a 10- $\mu\text{g}/\text{m}^3$ increase in PM_{2.5}.

The coefficient and standard error are estimated from the relative risk (1.14) and 95% confidence interval (1.07-1.22) associated with a 10- $\mu\text{g}/\text{m}^3$ increase in PM_{2.5} (Lepeule et al., 2012, Table 2).

Functional Form: Log-linear

Coefficient: 0.013103

Standard Error: 0.003347

Incidence Rate: county-specific annual all-cause mortality rate per person ages 25 and older

Population: population of ages 25 and older

Infant Mortality (Woodruff et al., 1997)

In a study of four million infants in 86 U.S. metropolitan areas conducted from 1989 to 1991, Woodruff et al. (1997) found a significant link between PM₁₀ exposure in the first two months of an infant's life with the probability of dying between the ages of 28 days and 364 days. PM₁₀ exposure was significant for all-cause mortality. PM₁₀ was also significant for respiratory mortality in average birth-weight infants, but not low birth-weight infants.

The coefficient and standard error are based on the odds ratio (1.04) and 95% confidence interval (1.02-1.07) associated with a 10 $\mu\text{g}/\text{m}^3$ change in PM₁₀ (Woodruff et al., 1997, Table 3).

Functional Form: Logistic

Coefficient: 0.003922

Standard Error: 0.001221

Incidence Rate: county-specific annual post-neonatal² infant deaths per infant under the age of one

Population: population of infants under one year old

² Post-neonatal refers to infants that are 28 days to 364 days old.

Non-Fatal Heart Attack

Non-fatal heart attacks have been linked with short-term exposures to PM_{2.5} in the U.S. (Peters et al., 2001) and other countries (Poloniecki, Atkinson, de Leon, & Anderson, 1997).³ We used the C-R functions reported in five studies as shown in Exhibit C-5.

The finding of a specific impact on heart attacks is consistent with hospital admission and other studies showing relationships between fine particles and cardiovascular effects both within and outside the U.S. These studies provide a weight of evidence for this type of effect. Several epidemiological studies (Gold et al., 2000; Liao et al., 1999; Magari et al., 2001) have shown that heart rate variability (an indicator of how much the heart is able to speed up or slow down in response to momentary stresses) is negatively related to PM_{2.5} levels. Lack of heart rate variability is a risk factor for heart attacks and other coronary heart diseases (Dekker et al., 2000; Liao et al., 1997; Tsuji et al., 1996). As such, the reduction in heart rate variability due to PM_{2.5} is consistent with an increased risk of heart attacks.

Exhibit C-5. Health Impact Functions for Particulate Matter and Non-fatal Heart Attack

Author	Year	Location	Age	Metric	Beta	Std Error	Functional Form
Peters et al.	2001	Boston, MA	18-99	24-hr avg	0.024121	0.009285	Logistic
Pope et al.	2006	Greater Salt Lake City, Utah	All	24-hr avg	0.00481	0.001992	Logistic
Sullivan et al.	2005	King County, Washington	All	24-hr avg	0.001980	0.002241	Logistic
Zanobetti and Schwartz	2006	Greater Boston area (Middlesex, Norfolk, Suffolk Counties)	All	24-hr avg	0.005300	0.002213	Logistic
Zanobetti et al.	2009	26 U.S. Communities	All	24-hr avg	0.00225	0.000592	Log-linear

COBRA reports two sets of incidence results: (1) incidence results based on C-R function from Peters et al. (2001); (2) pooled incidence based on other four studies using random/fixed effects pooling method.

Acute Myocardial Infarction (Heart Attacks), Nonfatal (Peters et al., 2001)

Peters et al. (2001) studied the relationship between increased particulate air pollution and onset of heart attacks in the Boston area from 1995 to 1996. The authors used air quality data for PM₁₀, PM_{10-2.5}, PM_{2.5}, “black carbon”, O₃, CO, NO₂, and SO₂ in a case-crossover analysis. For each subject, the case period was matched to three control periods, each 24 hours apart. In univariate analyses, the authors observed a positive association between heart attack occurrence and PM_{2.5} levels hours before and days before onset. The authors estimated multivariate conditional logistic

³ Non-fatal heart attacks are considered chronic illness although they are related to short-term exposure because the impact is long-lasting and this is reflected in its valuation (discussed in Appendix F).

models including two-hour and twenty-four hour pollutant concentrations for each pollutant. They found significant and independent associations between heart attack occurrence and both two-hour and twenty-four hour $PM_{2.5}$ concentrations before onset. Significant associations were observed for PM_{10} as well. None of the other particle measures or gaseous pollutants was significantly associated with acute myocardial infarction for the two hour or twenty-four hour period before onset.

The patient population for this study was selected from health centers across the United States. The mean age of participants was 62 years old, with 21% of the study population under the age of 50. In order to capture the full magnitude of heart attack occurrence potentially associated with air pollution and because age was not listed as an inclusion criteria for sample selection, we apply an age range of 18 and over in the C-R function. According to the National Hospital Discharge Survey, there were no hospitalizations for heart attacks among children <15 years of age in 1999 and only 5.5% of all hospitalizations occurred in 15-44 year olds (Popovic, 2001, Table 10).

The coefficient and standard error are calculated from an odds ratio of 1.62 (95% CI 1.13-2.34) for a $20 \mu\text{g}/\text{m}^3$ increase in twenty-four hour average $PM_{2.5}$ (Peters et al., 2001, Table 4, p. 2813).

Functional Form: Logistic

Coefficient: 0.024121

Standard Error: 0.009285

Incidence Rate: We use the county-specific daily AMI hospitalization rate (ICD-9 code 410) for the population of individuals aged 18 years and older as the estimate for the incidence rate of nonfatal heart attack, assuming all heart attacks that are not instantly fatal will result in a hospitalization. We did not adjust for fatal AMIs in the incidence rate estimation, due to the way that the epidemiological studies are designed. Those studies consider total admissions for AMIs, which includes individuals living at the time the studies were conducted. Therefore, we use the definition of AMI that matches the definition in the epidemiological studies.

Population: population of ages 18 and older

Adjustment: As some fraction of the admitted individuals die in the hospital, we apply a survival rate of 93% in calculating the avoided cases of AMI in order to avoid double counting (once in the calculation of AMI cases and once in the calculation of PM-related mortality).

Acute Myocardial Infarction (Heart Attacks), Nonfatal (Pope et al., 2006)

Pope et al. (2006) evaluated the association between short-term exposure to $PM_{2.5}$ and acute ischemic heart disease events, including acute nonfatal myocardial infarction, all acute coronary events, and subsequent myocardial infarctions in individuals living in greater Salt Lake City, Utah. In a case-crossover study, these ischemic events were assessed in relation to a $10 \mu\text{g}/\text{m}^3$ increase in $PM_{2.5}$.

Using a single-pollutant model the coefficient and standard error were estimated from the percent increase (4.81%) and 95% confidence interval (95% CI: 0.98-8.79) for a $10 \mu\text{g}/\text{m}^3$ increase in daily 24-hour mean $PM_{2.5}$ (Pope et al., 2006, Table 3).

Functional Form: Logistic

Coefficient: 0.00481

Standard Error: 0.001992

Incidence Rate: We use the county-specific daily AMI hospitalization rate (ICD-9 code 410) for the population of individuals aged 18 years and older as the estimate for the incidence rate of nonfatal heart attack, assuming all heart attacks that are not instantly fatal will result in a hospitalization. We did not adjust for fatal AMIs in the incidence rate estimation, due to the way that the epidemiological studies are designed. Those studies consider total admissions for AMIs, which includes individuals living at the time the studies were conducted. Therefore, we use the definition of AMI that matches the definition in the epidemiological studies.

Population: The study examined population of all ages. We apply the results to people ages 18 and older. We apply the results to people of ages 18 and older. Since the vast majority of AMI occur among population 65-99, over-counting may not be an issue when applying the risk coefficient to 18+.

Adjustment: As some fraction of the admitted individuals die in the hospital, we apply a survival rate of 93% in calculating the avoided cases of AMI in order to avoid double counting (once in the calculation of AMI cases and once in the calculation of PM-related mortality).

Acute Myocardial Infarction (Heart Attacks), Nonfatal (Sullivan et al., 2005)

Sullivan et al. (2005) studied the relationship between onset time of acute myocardial infarction and the preceding hourly PM_{2.5} concentrations in 5,793 confirmed cases of myocardial infarction through King County, Washington. In this case-crossover study from 1988-1994, air pollution exposure levels averaged 1 hour, 2 hours, 4 hours, and 24 hours before onset of myocardial infarction were compared to a set of time-stratified referent exposures from the same day of the week in the month of the case event. The authors estimated that an associated risk of 1.01 (95% CI: 0.98-1.05) for myocardial infarction onset could be attributed to a 10 µg/m³ increase in PM_{2.5} the hour before MI onset. No increased risk was found in all cases with preexisting cardiac diseases with an odds ratio of 1.05 (95% CI: 0.95-1.16). Furthermore, stratification for hypertension, diabetes, and smoking status did not modify the association between PM_{2.5} and onset of myocardial infarction.

Using a single-pollutant model, the coefficient and standard error were estimated from the odds ratio (1.02) and 95% confidence interval (95% CI: 0.98-1.07) for a 10 µg/m³ increase in daily 24-hour mean PM_{2.5} lagged 1 day (Sullivan et al., 2005, Table 3).

Functional Form: Logistic

Coefficient: 0.001980

Standard Error: 0.002241

Incidence Rate: We use the county-specific daily AMI hospitalization rate (ICD-9 code 410) for the population of individuals aged 18 years and older as the estimate for the incidence rate of nonfatal heart attack, assuming all heart attacks that are not instantly fatal will result in a hospitalization. We did not adjust for fatal AMIs in the incidence rate estimation, due to the way that the epidemiological studies are designed. Those studies consider total admissions for AMIs, which includes individuals living at the time the studies were conducted. Therefore, we use the definition of AMI that matches the definition in the epidemiological studies.

Population: The study examined population of all ages. We apply the results to people ages 18 and older. We apply the results to people of ages 18 and older. Since the vast majority of AMI

occur among population 65-99, over-counting may not be an issue when applying the risk coefficient to 18+.

Adjustment: As some fraction of the admitted individuals die in the hospital, we apply a survival rate of 93% in calculating the avoided cases of AMI in order to avoid double counting (once in the calculation of AMI cases and once in the calculation of PM-related mortality).

Acute Myocardial Infarction (Heart Attacks), Nonfatal (Zanobetti & Schwartz, 2006)⁴

Zanobetti and Schwartz (2006) analyzed hospital admissions through emergency department for myocardial infarction (ICD-9 code 410) and pneumonia (ICD-9 codes 480-487) for associations with fine particulate air pollution, ozone, black carbon, nitrogen dioxide, PM_{2.5} not from traffic, and CO in the greater Boston area from 1995-1999. The authors used a case-crossover analysis with control days matched on temperature. Significant associations were detected for NO₂ with a 12.7% increase (95% CI: 5.8-18.0), PM_{2.5} with an 8.6% increase (95% CI: 1.2-15.4), and black carbon with an 8.3% increase (95% CI: 0.2-15.8) in emergency myocardial infarction hospitalizations. Similarly, significant associations were identified for PM_{2.5} with a 6.5% increase (95% CI: 1.1-11.4) and CO with a 5.5% increase (95% CI: 1.1-9.5) in pneumonia hospitalizations.

Using a single-pollutant model, the coefficient and standard error are estimated from the percent change in risk (8.65%) and 95% confidence interval (95% CI: 1.22-15.38%) for a 16.32 ug/m³ increase in daily 24-hour mean PM_{2.5} for an average of the 0- and 1-day lag (Zanobetti & Schwartz, 2006, Table 4).

Functional Form: Logistic

Coefficient: 0.005300

Standard Error: 0.002213

Incidence Rate: We use the county-specific daily AMI hospitalization rate (ICD-9 code 410) for the population of individuals aged 18 years and older as the estimate for the incidence rate of nonfatal heart attack, assuming all heart attacks that are not instantly fatal will result in a hospitalization. We did not adjust for fatal AMIs in the incidence rate estimation, due to the way that the epidemiological studies are designed. Those studies consider total admissions for AMIs, which includes individuals living at the time the studies were conducted. Therefore, we use the definition of AMI that matches the definition in the epidemiological studies.

Population: The study examined population of ages 65 and older. We apply the results to people of ages 18 and older. Since the vast majority of AMI occur among population 65-99, over-counting may not be an issue when applying the risk coefficient to 18+.

Adjustment: As some fraction of the admitted individuals die in the hospital, we apply a survival rate of 93% in calculating the avoided cases of AMI in order to avoid double counting (once in the calculation of AMI cases and once in the calculation of PM-related mortality).

⁴ The study looked at hospital admissions of AMI through ER. Under the assumption that all heart attacks will end in hospitalization, we consider the endpoint as heart attack events to be consistent with other studies.

Acute Myocardial Infarction (Heart Attacks), Nonfatal (Zanobetti et al., 2009)

Zanobetti et al. (2009) examined the relationship between daily PM_{2.5} levels and emergency hospital admissions for cardiovascular causes, myocardial infarction, congestive heart failure, respiratory disease and diabetes among 26 U.S. communities from 2000-2003. The authors used meta-regression to examine how this association was modified by season- and community-specific PM_{2.5} composition while controlling for seasonal temperature as a substitute for ventilation. Overall, the authors found that PM_{2.5} mass higher in Ni, As, and Cr as well as Br and organic carbon significantly increased its effects on hospital admissions. For a 10 ug/m³ increase in 2-day averaged PM_{2.5}, a 1.89% (95% CI: 1.34-2.45) increase in cardiovascular disease admissions, a 2.25% (95% CI: 1.10-3.42) increase in myocardial infarction admissions, a 1.85% (95% CI: 1.19-2.51) increase in congestive heart failure admissions, a 2.74% (95% CI: 1.30-4.20) increase in diabetes admissions, and a 2.07% (95% CI: 1.20-2.95) increase in respiratory admissions were observed. The relationship between PM_{2.5} and cardiovascular admissions was significantly modified when the mass of PM_{2.5} was high in Br, Cr, Ni, and sodium ions, while mass high in As, Cr, Mn, organic carbon, Ni and sodium ions modified the myocardial infarction relationship and mass high in As, organic carbon, and sulfate ions modified the diabetes admission rates.

Using a single-pollutant model, the coefficient and standard error are estimated from the percent change in risk (2.25%) and 95% confidence interval (95% CI: 1.10-3.42) for a 10 ug/m³ increase in 2-day averaged PM_{2.5} (Zanobetti et al., 2009, Table 3).

Functional Form: Log-linear

Coefficient: 0.00225

Standard Error: 0.000592

Incidence Rate: We use the county-specific daily AMI hospitalization rate (ICD-9 code 410) for the population of individuals aged 18 years and older as the estimate for the incidence rate of nonfatal heart attack, assuming all heart attacks that are not instantly fatal will result in a hospitalization. We did not adjust for fatal AMIs in the incidence rate estimation, due to the way that the epidemiological studies are designed. Those studies consider total admissions for AMIs, which includes individuals living at the time the studies were conducted. Therefore, we use the definition of AMI that matches the definition in the epidemiological studies.

Population: The study examined population of ages 65 and older. We apply the results to people of ages 18 and older. Since the vast majority of AMI occur among population 65-99, over-counting may not be an issue when applying the risk coefficient to 18+.

Adjustment: As some fraction of the admitted individuals die in the hospital, we apply a survival rate of 93% in calculating the avoided cases of AMI in order to avoid double counting (once in the calculation of AMI cases and once in the calculation of PM-related mortality).

Hospitalizations

We include two main types of hospital admissions – respiratory (all respiratory, COPD, and asthma) and cardiovascular (all cardiovascular less myocardial infarctions).

Respiratory and cardiovascular hospital admissions are the two broad categories of hospital admissions that have been related to PM_{2.5} exposure. Although the benefits associated with respiratory and cardiovascular hospital admissions are estimated separately in the analysis, the methods used to estimate changes in incidence and to value those changes are the same for both broad categories of hospital admissions.

Due to the availability of detailed hospital admission and discharge records, there is an extensive body of literature examining the relationship between hospital admissions and air pollution. Because of this, we pooled some of the hospital admission endpoints, using the results from a number of studies. Specifically, we used the following pooling procedure.

- For respiratory hospital admissions (HA): Babin et al. (2007) and Sheppard (2003) were used to estimate C-R functions for asthma hospitalizations (ICD-9 code: 493) for ages 0-18 in Washington D.C and Seattle, WA, respectively. We pooled the C-R functions from these two studies using the random/fixed effects method. We then pooled results from Zanobetti et al. (2009) and Kloog et al. (2012) using subjective weights pooling method (i.e., 0.5 for each study) to estimate incidence for all-respiratory admissions for the elderly (age 65 and up). We then aggregated incidence estimates from the following three non-overlapping categories: (1) pooled asthma hospitalization (ages 0-18) from above, (2) pooled all-respiratory admissions for the elderly (age 65 and up) from above, and (3) COPD less asthma admissions for ages 18-64 from Moolgavkar (2000a).
- For HA for cardiovascular diseases less myocardial infarctions (ICD-9 codes: 390-409, 411-429): Peng et al. (2008) and Peng et al. (2009) reported C-R functions for people age 65 years and older in 108 U.S. counties and 119 U.S. urban counties, respectively. We assigned equal weights to the estimates from these two studies (i.e., 0.5 for each study) and used the weighted average. We then assigned a weight of 0.33 to the results from each of two other studies that look at population of 65 years and older – Zanobetti et al. (2009) and Bell et al. (2008) – and pooled these results with the pooled results from Peng et al. (2008) and Peng et al. (2009).

Exhibit C-6. Health Impact Functions for Particulate Matter and Hospital Admissions

Endpoint	Author	Year	Location	Age	Metric	Beta	Std Error	Functional Form
All Cardiovascular (less AMI) ^a	Zanobetti et al.	2009	26 U.S. communities	65+	24-hr avg	0.00189	0.00028	Log-linear
All Cardiovascular (less AMI) ^a	Peng et al.	2008	108 U.S. counties	65+	24-hr avg	0.00071	0.00013	Log-linear
All Cardiovascular (less AMI) ^a	Peng et al.	2009	119 U.S. urban counties	65+	24-hr avg	0.00068	0.00021	Log-linear
All Cardiovascular (less AMI) ^a	Bell et al.	2008	202 US Counties	65+	24-hr avg	0.0008	0.00011	Log-linear
All Cardiovascular (less AMI) ^a	Moolgavkar	2000b	Los Angeles, CA	18-64	24-hr avg	0.0014	0.00034	Log-linear
HA, All Respiratory ^b	Zanobetti et al.	2009	26 U.S. communities	65+	24-hr avg	0.00207	0.00045	Log-linear
HA, All Respiratory ^b	Kloog et al.	2012	New England area (6 states)	65+	24-hr avg	0.0007	0.00096	Log-linear
HA, Asthma ^b	Babin et al.	2007	Washington, D.C.	0-17	24-hr avg	0.002	0.00434	Log-linear
HA, Asthma ^b	Sheppard	2003	Seattle, WA	0-17	24-hr avg	0.00332	0.00104	Log-linear
HA, COPD ^b	Moolgavkar	2000a	Los Angeles, CA	18-64	24-hr avg	0.0022	0.00073	Log-linear

^a These studies were pooled to generate pooled incidence estimates for cardiovascular hospital admissions.

^b These studies were pooled to generate pooled incidence estimates for respiratory hospital admissions.

Hospital Admissions for All Cardiovascular (Bell et al., 2008)

Bell et al. (2008) evaluated the association between short-term exposure to PM_{2.5} and the risk of cardiovascular (ICD-9 codes 410-414, 26-427, 428, 429, 430-438, and 440-449) hospital admissions among Medicare enrollees ≥65 years old varied by season and geographic region in 202 U.S. counties with populations greater than 200,000 from 1999-2005. Three time-series models were used to provide three key variables: consistent PM_{2.5} effects across the year, different PM_{2.5} effects by season, and smoothly varying PM_{2.5} effects throughout the year. A two-stage Bayesian hierarchical model was used to estimate the association between PM_{2.5} and hospitalization rates, with the first stage estimating the association within a single county and the second stage combining county-specific estimates to obtain national estimates. The authors found statistically significant evidence of seasonal and regional variation. The strongest association was for the northeast.

We use the national estimate for the all-year reported in Table 2 of Bell et al. (2008). The single pollutant coefficient and standard error are calculated from the estimated 0.8 percent increase in risk and 95% confidence interval (0.59-1.01 percent) for a 10 µg/m³ increase in same-day (lag 0) daily 24-hour mean PM_{2.5} (Bell et al., 2008, Table 2).

Note that Bell et al. (2008) considered a broader range of ICD-9 codes and estimated the risk of both cardiovascular events and cerebro- and peripheral vascular disease. For comparability to

other studies, EPA decided to apply a baseline hospitalization rate for ICD-9 codes 390-409 and 411-429 when using this C-R function in quantifying impacts.

Functional Form: Log-linear

Coefficient: 0.0008

Standard Error: 0.00011

Incidence Rate: county-specific daily hospital admission rate for all cardiovascular admissions less AMI per person ages 65+ (ICD-9 codes 390-409, 411-429)

Population: population of ages 65+

Hospital Admissions for All Cardiovascular (Peng et al., 2008)

Peng et al. (2008) examined the risk of hospital admissions for cardiovascular diseases (ICD-9 codes 426-427, 428, 430-438, 410-414, 429, 440-448) in relation to particulate matter (PM_{10-2.5} and PM_{2.5}). To accomplish this, the authors utilized a database of 108 U.S. counties with daily emergency hospital admission rates for cardiovascular diseases among Medicare enrollees living 9 miles from air, temperature, and dew-point temperature monitors. PM_{10-2.5} and PM_{2.5} concentrations were calculated by using monitoring data from January 1, 1999 through December 31, 2005. Overall, there were 3.7 million cardiovascular disease-related hospital admissions for the time period assessed. The authors found significant associations of PM_{2.5} and PM_{10-2.5} with cardiovascular disease admissions.

In a single-pollutant model, the coefficient and standard error are calculated from the estimated percent change in daily admission (0.44%) and 95% posterior interval (95% PI: 0.06-0.82%) for a 10 µg/m³ increase in daily 24-hour mean PM_{2.5} concentrations for the same day (Peng et al., 2008, page 2175).

Note that Peng et al. (2008) considered a broader range of ICD-9 codes and estimated the risk of both cardiovascular events and cerebro- and peripheral vascular disease. For comparability to other studies, EPA decided to apply a baseline hospitalization rate for ICD-9 codes 390-409 and 411-429 when using this C-R function in quantifying impacts.

Functional Form: Log-linear

Coefficient: 0.00071

Standard Error: 0.00013

Incidence Rate: county-specific daily hospital admission rate for all cardiovascular admissions less AMI per person ages 65+ (ICD-9 codes 390-409, 411-429)

Population: population of ages 65+

Hospital Admissions for All Cardiovascular (Peng et al., 2009)

Peng et al. (2009) investigated the relationship between hospital admissions for cardiovascular and the chemical components of PM_{2.5} across 119 U.S. urban communities for 12 million Medicare enrollees using log-linear Poisson regression models. This was achieved using a national database with daily data from 2000-2006 on emergency hospital admissions of cardiovascular outcomes, ambient levels of PM_{2.5} components and weather variables. Bayesian hierarchical statistical models were used to estimate the associations. Three scenarios for PM_{2.5}

exposure were assessed which were as follows: 1) for the period 2000-2006 and including only days with available measurements for all 7 PM_{2.5} components from the Speciation Trends network (STN); 2) PM_{2.5} measured by the STN for the period 2000-2006 and including only days with available measurements for all 7 PM_{2.5} components from the STN and 3) PM_{2.5} estimated as the sum of the 7 largest components of PM_{2.5} mass for the period 2000-2006. Results of percent increases in emergency admissions associated with PM_{2.5} at lag 0 under these scenarios were showed in Figure 2 and the results for the components of PM_{2.5} from both single and multi-pollutant models were showed in Figure 3.

In a single-pollutant model, the coefficient and standard error are calculated from the estimated percent change in daily admission (0.68%) and 95% posterior interval (95% PI: 0.26-1.10%) for a 10 µg/m³ increase in daily 24-hour mean PM_{2.5} concentrations for the same day (Peng et al., 2009, page 960).

Note that Peng et al. (2008) considered a broader range of ICD-9 codes and estimated the risk of both cardiovascular events and cerebro- and peripheral vascular disease. For comparability to other studies, EPA decided to apply a baseline hospitalization rate for ICD-9 codes 390-409 and 411-429 when using this C-R function in quantifying impacts.

Functional Form: Log-linear

Coefficient: 0.00068

Standard Error: 0.00021

Incidence Rate: county-specific daily hospital admission rate for all cardiovascular admissions less AMI per person ages 65+ (ICD-9 codes 390-409, 411-429)

Population: population of ages 65+

Hospital Admissions for All Cardiovascular (Zanobetti et al., 2009)

Zanobetti et al. (2009) examined the relationship between daily PM_{2.5} levels and emergency hospital admissions for cardiovascular causes, myocardial infarction, congestive heart failure, respiratory disease and diabetes among 26 U.S. communities from 2000-2003. The authors used meta-regression to examine how this association was modified by season- and community-specific PM_{2.5} composition while controlling for seasonal temperature as a substitute for ventilation. Overall, the authors found that PM_{2.5} mass higher in Ni, As, and Cr as well as Br and organic carbon significantly increased its effects on hospital admissions. The relationship between PM_{2.5} and cardiovascular admissions was significantly modified when the mass of PM_{2.5} was high in Br, Cr, Ni, and sodium ions, while mass high in As, Cr, Mn, organic carbon, Ni and sodium ions modified the myocardial infarction relationship and mass high in As, organic carbon, and sulfate ions modified the diabetes admission rates.

The single-pollutant coefficient and standard error are calculated from the estimated percent change in risk (1.89 percent) and 95% confidence interval (1.34-2.45) for a 10 µg/m³ increase in 2-day averaged PM_{2.5} (Zanobetti et al., 2009, Table 3).

Note that Zanobetti et al. (2009) report results for ICD-9 codes 390-429. In the benefit analysis, avoided nonfatal heart attacks are estimated separately. In order to avoid double counting heart

attack hospitalizations, we have excluded ICD-9 code 410 from the baseline incidence rate used in this function.

Functional Form: Log-linear

Coefficient: 0.00189

Standard Error: 0.00028

Incidence Rate: county-specific daily hospital admission rate for all cardiovascular admissions less AMI per person ages 65+ (ICD-9 codes 390-409, 411-429)

Population: population of ages 65+

Hospital Admissions for All Cardiovascular (Moolgavkar, 2000b)

Moolgavkar (2000b) examined the association between air pollution and cardiovascular hospital admissions (ICD-9 390-448) in the Chicago, Los Angeles, and Phoenix metropolitan areas. He collected daily air pollution data for ozone, SO₂, NO₂, CO, and PM₁₀ in all three areas. PM_{2.5} data was available only in Los Angeles. The data were analyzed using a Poisson regression model with generalized additive models to adjust for temporal trends. Separate models were run for 0 to 5 day lags in each location. In a single pollutant model, PM_{2.5} was statistically significant for lag 0 and lag 1. In co-pollutant models with CO, the PM_{2.5} effect dropped out and CO remained significant. For ages 20-64, SO₂ and CO exhibited the strongest effect and any PM_{2.5} effect dropped out in co-pollutant models with CO. Among the 65+ age group, the gaseous pollutants generally exhibited stronger effects than PM₁₀ or PM_{2.5}. The strongest overall effects were observed for SO₂ and CO.

The single pollutant coefficient and standard error are calculated from an estimated percent change of 1.4 and t-statistic of 4.1 for a 10 µg/m³ increase in PM_{2.5} in the zero lag model for ages 18-64 (Moolgavkar, 2000b, Table 4).

Note that Moolgavkar (2000b) reported results that include ICD-9 code 410 (heart attack). In the benefits analysis, avoided nonfatal heart attacks are estimated separately. In order to avoid double counting heart attack hospitalizations, we have excluded ICD-9 code 410 from the baseline incidence rate used in this function.

Functional Form: Log-linear

Coefficient: 0.0014

Standard Error: 0.000341

Incidence Rate: county-specific daily hospital admission rate for all cardiovascular admissions per person ages 18 to 64 (ICD-9 codes 390-409, 411-429)

Population: population of ages 18 to 64

Hospital Admissions for All Respiratory (Zanobetti et al., 2009)

Zanobetti et al. (2009) examined the relationship between daily PM_{2.5} levels and emergency hospital admissions for cardiovascular causes, myocardial infarction, congestive heart failure, respiratory disease and diabetes among 26 U.S. communities from 2000-2003. The authors used meta-regression to examine how this association was modified by season- and community-specific PM_{2.5} composition while controlling for seasonal temperature as a substitute for

ventilation. Overall, the authors found that PM_{2.5} mass higher in Ni, As, and Cr as well as Br and organic carbon significantly increased its effects on hospital admissions. The relationship between PM_{2.5} and cardiovascular admissions was significantly modified when the mass of PM_{2.5} was high in Br, Cr, Ni, and sodium ions, while mass high in As, Cr, Mn, organic carbon, Ni and sodium ions modified the myocardial infarction relationship and mass high in As, organic carbon, and sulfate ions modified the diabetes admission rates.

In a single-pollutant model, the coefficient and standard error are estimated from the percent change in risk (2.07%) and 95% confidence interval (1.2% - 2.95%) for a 10 µg/m³ increase in 2-day averaged PM_{2.5} (Zanobetti et al., 2009, Table 3).

Functional Form: Log-linear

Coefficient: 0.00207

Standard Error: 0.00045

Incidence Rate: county-specific daily hospital admission rate for all respiratory admissions per person ages 65+ (ICD-9 codes 460 - 519)

Population: population of ages 65+

Hospital Admissions for All Respiratory (Kloog et al., 2012)

Kloog et al. (2012) investigated both the long and short term effects of PM_{2.5} exposure on hospital admissions across New England for all residents aged 65 and older. The authors performed separate Poisson regression analysis for each admission type: all respiratory, cardiovascular disease (CVD), stroke and diabetes. Daily admission counts in each zip code were regressed against long and short-term PM_{2.5} exposure, temperature, socio-economic data and a spline of time to control for seasonal trends in baseline risk. They observed associations between both short-term and long-term exposure to PM_{2.5} and hospitalization for all of the outcomes examined.

In a single-pollutant model, the coefficient and standard error are estimated from the percent change in risk (0.70%) and 95% confidence interval (0.35% - 0.52%) for a 10 µg/m³ increase in short-term (same day) PM_{2.5} exposure (Kloog et al., 2012, Table 3).

Functional Form: Log-linear

Coefficient: 0.0007

Standard Error: 0.00096

Incidence Rate: county-specific daily hospital admission rate for all respiratory admissions per person ages 65+ (ICD-9 codes 460 - 519)

Population: population of ages 65+

Hospital Admissions for Asthma (Sheppard, 2003)

Sheppard et al. (1999) studied the relation between air pollution in Seattle and nonelderly (<65) hospital admissions for asthma from 1987 to 1994. They used air quality data for PM₁₀, PM_{2.5}, coarse PM_{10-2.5}, SO₂, ozone, and CO in a Poisson regression model with control for time trends,

seasonal variations, and temperature-related weather effects.⁵ They found asthma hospital admissions associated with PM₁₀, PM_{2.5}, PM_{10-2.5}, CO, and ozone. They did not observe an association for SO₂. They found PM_{2.5} and CO to be jointly associated with asthma admissions. The best fitting co-pollutant models were found using ozone. However, ozone data was only available April through October, so they did not consider ozone further. For the remaining pollutants, the best fitting models included PM_{2.5} and CO. Results for other co-pollutant models were not reported.

In response to concerns that the work by Sheppard et al. (1999) may be biased because of concerns about the (S-plus) software used in the original analysis, Sheppard (2003) reanalyzed some of this work; in particular Sheppard reanalyzed the original study's PM_{2.5} single pollutant model.

The coefficient and standard error are based on the relative risk (1.04) and 95% confidence interval (1.01-1.06) for a 11.8 µg/m³ increase in PM_{2.5} in the 1-day lag GAM stringent model (Sheppard, 2003, pp 228-299).

Functional Form: Log-linear

Coefficient: 0.003324

Standard Error: 0.001045

Incidence Rate: county-specific daily hospital admission rate for asthma admissions per person (ICD-9 code 493)

Population: population of ages 0 -17⁶

Hospital Admissions for Asthma (Babin et al., 2007)

Babin et al. (2007) examined pediatric asthma-related emergency room (ER) visits and hospital admissions (ICD-9 code 493) in Washington, D.C. from 2001-2004 and their short-term associations with ozone, particulate matter, socioeconomic status, and age group. Applying Poisson regression analyses, the authors found significant associations between asthma ER visits and outdoor ozone concentrations for the 5-12 year old age group. The association between PM_{2.5} and asthma hospitalization was found statistically insignificant.

The single pollutant coefficient and standard error are calculated from the estimated percent increase in risk (0.2 percent) and 95% confidence interval (-0.6 – 0.1 percent) for a 1 µg/m³ increase in same-day (lag 0) daily 24-hour mean PM_{2.5} based on single-pollutant models (Babin et al., 2007, Table 2).

Functional Form: Log-linear

Coefficient: 0.002

Standard Error: 0.00434

⁵ PM_{2.5} levels were estimated from light scattering data.

⁶ Although Sheppard (2003) reports results for the <65 year old age range, for comparability to other studies, we apply the results to the population of ages 0 to 18.

Incidence Rate: county-specific daily hospital admission rate for asthma admissions per person (ICD-9 code 493)

Population: population of ages 0 -17

Hospital Admissions for Chronic Lung Disease (Moolgavkar, 2000a)

Moolgavkar (2000a) examined the association between air pollution and COPD hospital admissions (ICD-9 490-496) in the Chicago, Los Angeles, and Phoenix metropolitan areas. He collected daily air pollution data for ozone, SO₂, NO₂, CO, and PM₁₀ in all three areas. PM_{2.5} data was available only in Los Angeles. The data were analyzed using a Poisson regression model with generalized additive models to adjust for temporal trends. Separate models were run for 0 to 5 day lags in each location. Among the 65+ age group in Chicago and Phoenix, weak associations were observed between the gaseous pollutants and admissions. No consistent associations were observed for PM₁₀. In Los Angeles, marginally significant associations were observed for PM_{2.5}, which were generally lower than for the gases. In co-pollutant models with CO, the PM_{2.5} effect was reduced. Similar results were observed in the 0-19 and 20-64 year old age groups.

The PM_{2.5} C-R functions for the 20-64 age group are based on the single-pollutant model. Since the true PM_{2.5} effect is most likely best represented by a distributed lag model, any single lag model should underestimate the total PM_{2.5} effect. As a result, we selected the lag models with the greatest effect estimates for use in the C-R functions.

The single pollutant coefficient and standard error are calculated from an estimated percent change of 2.2 and t-statistic of 3.0 for a 10 µg/m³ increase in PM_{2.5} in the two-day lag model (Moolgavkar, 2000a, Table 4).

Functional Form: Log-linear

Coefficient: 0.0022

Standard Error: 0.000733

Incidence Rate: county-specific daily hospital admission rate for chronic lung disease admissions per person 18-64 (ICD-9 codes 490-496)

Population: population of ages 18 to 64⁷

⁷ Although Moolgavkar (2000a) reports results for the 20-64 year old age range, for comparability to other studies, we apply the results to the population of ages 18 to 64.

Emergency Room Visits

To estimate the effects of PM_{2.5} air pollution reductions on asthma-related ER visits, we use the C-R functions based on Mar et al. (2010), Slaughter et al. (2005) and Glad et al. (2012). COBRA estimates the incidence results for ER visits by pooling these three studies using random/fixed pooling method. Exhibit C-7 below summarizes the attributes of the C-R functions used in COBRA.

Exhibit C-7. Health Impact Functions for Particulate Matter and Emergency Room Visits

Author	Year	Location	Age	Metric	Beta	Std Error	Functional Form
Mar et al.	2010	Greater Tacoma, Washington	0-99	24-hr avg	0.0056	0.0021	Log-linear
Slaughter et al.	2005	Spokane, Washington	0-99	24-hr avg	0.0029	0.0027	Log-linear
Glad et al.	2012	Pittsburgh, PA	0-99	24-hr avg	0.0039	0.0028	Logistic

Emergency Room Visits for Asthma (Mar et al., 2010)

Mar et al. (2010) assessed the effect of particulate matter air pollution, including emissions from diesel generators, on emergency room visits for asthma in the greater Tacoma, Washington area from January 3, 1998 to May 30, 2002 using Poisson regression models. Health data were collected for individuals of all ages from 6 Tacoma hospitals. The authors also assessed the impacts of diesel generator use on emergency room visits for asthma from January 24, 2001 to June 2, 2001. Overall, the researchers found an association between daily PM_{2.5} levels and emergency room visits for asthma at lag days 2 and 3, with a relative risk for lag day 2 of 1.04 (95% CI: 1.01-1.07) and a relative risk for lag day 3 of 1.03 (95% CI: 1.0-1.06). No significant association between emergency room visits for asthma and increased use of the diesel generators was observed.

In a single-pollutant model, the PM_{2.5} coefficient and standard error are estimated from the relative risk (1.04) and 95% confidence interval (95% CI: 1.01-1.07) for a 7 µg/m³ increase in daily 24-hour mean PM_{2.5} at lag day 2 (Mar et al., 2010, Table 4).

Functional Form: Log-linear

Coefficient: 0.0056

Standard Error: 0.0021

Incidence Rate: county-specific daily asthma emergency room rate per person (The study didn't report ICD-9 code but we assume ICD-9 code 493)

Population: population of all ages

Emergency Room Visits for Asthma (Slaughter et al., 2005)

Slaughter et al. (2005) examined the short-term association of particulate matter (PM₁, PM_{2.5}, PM₁₀, and PM_{10-2.5}) and carbon monoxide with hospital admissions and emergency room visits for respiratory and cardiac outcomes and mortality in Spokane, Washington from January 1995

to June 2001 using a log-linear generalized linear model. The authors found no association between respiratory emergency room visits and any size fraction of PM_{2.5}, but there was a suggestive relationship between fine PM_{2.5} and respiratory effects when compared to coarse PM_{2.5}. No association between cardiac hospital admissions or mortality and any size fraction of PM_{2.5} or CO was observed at the 0- to 3-day lag. CO, on the other hand, was found to be associated with all respiratory emergency room visits and visits for asthma at the 3-day lag.

In a single-pollutant model, the coefficient and standard error are estimated from the relative risk (1.03) and 95% confidence interval (95% CI: 0.98-1.09) for a 10 µg/m³ increase in daily 24-hour mean PM_{2.5} at 1-day lag (Slaughter et al., 2005, Table 4).

Functional Form: Log-linear

Coefficient: 0.0029

Standard Error: 0.0027

Incidence Rate: county-specific daily asthma emergency room rate per person (ICD-9 code 493)

Population: population of all ages

Emergency Room Visits for Asthma (Glad et al., 2012)

Glad et al. (2012) investigated the relationship between air pollution and emergency department (ED) visits for asthma in the Pittsburgh, Pennsylvania area between 2002 and 2005 using a case-crossover methodology with a logistical model. The authors found a 2.5% increase in asthma ED visits for each 10 ppb increase in the 1-hour maximum ozone level on day 2 (odds ratio [OR] = 1.025, $p < .05$). Particulate matter with an aerodynamic diameter ≤ 2.5 µm (PM_{2.5}) had an effect both on the total population on day 1 after exposure (1.036, $p < .05$), and on African Americans on days 1, 2, and 3. PM_{2.5} had no significant effect on Caucasian Americans alone. The disparity in risk estimates by race may reflect differences in residential characteristics, exposure to ambient air pollution, or a differential effect of pollution by race.

In a single-pollutant model, the coefficient and standard error are estimated from the relative risk (1.040) and 95% confidence interval (95% CI: 0.984-1.100) for a 10 µg/m³ increase 6-day average of daily PM_{2.5} (Glad et al., 2012, Table 3).

Functional Form: Logistic

Coefficient: 0.0039

Standard Error: 0.0028

Incidence Rate: county-specific daily asthma emergency room rate per person (ICD-9 code 493)

Population: population of all ages

Minor Effects

We include functions to estimate acute bronchitis, lower respiratory symptoms, minor restricted days, and work loss days.

Exhibit C-8. Health Impact Functions for Particulate Matter and Acute Effects

Endpoint Name	Author	Year	Location	Age	Metric	Beta	Std Error	Functional Form
Minor Restricted Activity Days	Ostro & Rothschild	1989	Nationwide	18-64	24-hr avg	0.007410	0.000700	Log-linear
Acute Bronchitis	Dockery et al.	1996	24 communities	8-12	Annual	0.027212	0.017096	Logistic
Work Loss Days	Ostro	1987	Nationwide	18-64	24-hr avg	0.004600	0.000360	Log-linear
Lower Respiratory Symptoms	Schwartz and Neas	2000	6 U.S. cities	7-14	24-hr avg	0.019012	0.006005	Logistic

Acute Bronchitis (Dockery et al., 1996)

Dockery et al (1996) examined the relationship between $PM_{2.5}$ and other pollutants on the reported rates of asthma, persistent wheeze, chronic cough, and bronchitis, in a study of 13,369 children ages 8-12 living in 24 communities in U.S. and Canada. Health data were collected in 1988-1991, and single-pollutant models were used in the analysis to test a number of measures of particulate air pollution. Dockery et al. found that annual level of sulfates and particle acidity were significantly related to bronchitis, and $PM_{2.1}$ and PM_{10} were marginally significantly related to bronchitis.⁸ They also found nitrates were linked to asthma, and sulfates linked to chronic phlegm. It is important to note that the study examined annual pollution exposures, and the authors did not rule out that acute (daily) exposures could be related to asthma attacks and other acute episodes. Earlier work, by Dockery et al. (1989), based on six U.S. cities, found acute bronchitis and chronic cough significantly related to PM_{15} . Because it is based on a larger sample, the Dockery et al (1996) study is the better study to develop a C-R function linking $PM_{2.5}$ with bronchitis.

Bronchitis was counted in the study only if there were “reports of symptoms in the past 12 months” (Dockery et al., 1996, p. 501). It is unclear, however, if the cases of bronchitis are acute and temporary, or if the bronchitis is a chronic condition. Dockery et al. found no relationship between $PM_{2.5}$ and chronic cough and chronic phlegm, which are important indicators of chronic bronchitis. For this analysis, we assumed that the health impact function based on Dockery et al. is measuring acute bronchitis. The health impact function is based on results of the single pollutant model reported in Table 1.

⁸ The original study measured $PM_{2.1}$, however when using the study's results we use $PM_{2.5}$. This makes only a negligible difference, assuming that the adverse effects of $PM_{2.1}$ and $PM_{2.5}$ are comparable.

The estimated logistic coefficient and standard error are based on the odds ratio (1.50) and 95% confidence interval (0.91-2.47) associated with being in the most polluted city ($PM_{2.1} = 20.7 \mu\text{g}/\text{m}^3$) versus the least polluted city ($PM_{2.1} = 5.8 \mu\text{g}/\text{m}^3$) (Dockery et al., 1996, Tables 1 and 4). The original study used $PM_{2.1}$, however, we use the $PM_{2.1}$ coefficient and apply it to $PM_{2.5}$ data.

Functional Form: Logistic

Coefficient: 0.027212

Standard Error: 0.017096

Incidence Rate: annual bronchitis incidence rate per person = 0.043 (American Lung Association, 2002, Table 11)

Population: population of ages 8-12

Lower Respiratory Symptoms (Schwartz & Neas, 2000)

Schwartz and Neas (2000) used logistic regression to link lower respiratory symptoms and cough in children with coarse PM_{10} , $PM_{2.5}$, sulfate and H^+ (hydrogen ion). Children were selected for the study if they were exposed to indoor sources of air pollution: gas stoves and parental smoking. The study enrolled 1,844 children into a year-long study that was conducted in different years (1984 to 1988) in six cities. The students were in grades two through five at the time of enrollment in 1984. By the completion of the final study, the cohort would then be in the eighth grade (ages 13-14); this suggests an age range of 7 to 14.

The coefficient and standard error are calculated from the reported odds ratio (1.33) and 95% confidence interval (1.11-1.58) associated with a $15 \mu\text{g}/\text{m}^3$ change in $PM_{2.5}$ (Schwartz & Neas, 2000, Table 2).

Functional Form: Logistic

Coefficient: 0.01901

Standard Error: 0.006005

Incidence Rate: daily lower respiratory symptom incidence rate per person = 0.0012 (Schwartz et al., 1994, Table 2).

Population: population of ages 7 to 14

Minor Restricted Activity Days (Ostro and Rothschild, 1989)

Ostro and Rothschild (1989) estimated the impact of $PM_{2.5}$ and ozone on the incidence of minor restricted activity days (MRADs) and respiratory-related restricted activity days (RRADs) in a national sample of the adult working population, ages 18 to 65, living in metropolitan areas.⁹ The annual national survey results used in this analysis were conducted in 1976-1981. Controlling for $PM_{2.5}$, two-week average ozone has highly variable association with RRADs and MRADs.

⁹ The study population is based on the Health Interview Survey (HIS), conducted by the National Center for Health Statistics. In publications from this ongoing survey, non-elderly adult populations are generally reported as ages 18-64. From the study, it is not clear if the age range stops at 65 or includes 65 year olds. We apply the health impact function to individuals ages 18-64 for consistency with other studies estimating impacts to non-elderly adult populations.

Controlling for ozone, two-week average PM_{2.5} was significantly linked to both health endpoints in most years.¹⁰ The health impact function for PM_{2.5} is based on this co-pollutant model.

The study is based on a “convenience” sample of non-elderly individuals. Applying the health impact function to this age group is likely a slight underestimate, as it seems likely that elderly are at least as susceptible to PM_{2.5} as individuals under 65.

Using the results of the two-pollutant model (O₃ and PM_{2.5}), we developed separate coefficients for each year in the analysis, which were then combined for use in this analysis. The coefficient is a weighted average of the coefficients in Ostro and Rothschild (1989, Table 4) using the inverse of the variance as the weight:

$$\beta = \frac{\sum_{i=1976}^{1981} \frac{\beta_i}{\sigma_{\beta_i}^2}}{\sum_{i=1976}^{1981} \frac{1}{\sigma_{\beta_i}^2}} = 0.00741$$

The standard error of the coefficient is calculated as follows, assuming that the estimated year-specific coefficients are independent:

$$\sigma_{\beta}^2 = \text{Var} \left(\frac{\sum_{i=1976}^{1981} \frac{\beta_i}{\sigma_{\beta_i}^2}}{\sum_{i=1976}^{1981} \frac{1}{\sigma_{\beta_i}^2}} \right) = \text{Var} \left(\frac{\sum_{i=1976}^{1981} \frac{\beta_i}{\sigma_{\beta_i}^2}}{\gamma} \right) = \sum_{i=1976}^{1981} \text{Var} \left(\frac{\beta_i}{\gamma \cdot \sigma_{\beta_i}^2} \right)$$

This reduces down to:

$$\sigma_{\beta} = \sqrt{1/\gamma} = 0.00070$$

Functional Form: Log-linear

Coefficient: 0.00741

Standard Error: 0.00070

Incidence Rate: daily incidence rate for minor restricted activity days (MRAD) = 0.02137 (Ostro & Rothschild, 1989, p. 243).

Population: adult population ages 18 to 64

Work Loss Days (Ostro, 1987)

Ostro (1987) estimated the impact of PM_{2.5} on the incidence of work-loss days (WLDs), restricted activity days (RADs), and respiratory-related RADs (RRADs) in a national sample of the adult working population, ages 18 to 65, living in metropolitan areas.¹¹ The annual national

¹⁰ The study used a two-week average pollution concentration; the health impact function uses a daily average, which is assumed to be a reasonable approximation.

¹¹ The study population is based on the Health Interview Survey (HIS), conducted by the National Center for Health Statistics. In publications from this ongoing survey, non-elderly adult populations are generally reported as ages 18-64. From the study, it is not clear if the age range stops at 65 or includes 65 year olds. We apply the health impact function to individuals ages 18-64 for consistency with other studies estimating impacts to non-elderly adult populations.

survey results used in this analysis were conducted in 1976-1981. Ostro reported that two-week average PM_{2.5} levels¹² were significantly linked to work-loss days, RADs, and RRADs, however there was some year-to-year variability in the results. Separate coefficients were developed for each year in the analysis (1976-1981); these coefficients were pooled. The coefficient used in the concentration-response function presented here is a weighted average of the coefficients in Ostro (1987, Table 3) using the inverse of the variance as the weight.

The study is based on a “convenience” sample of non-elderly individuals. Applying the health impact function to this age group is likely a slight underestimate, as it seems likely that elderly are at least as susceptible to PM_{2.5} as individuals under 65. On the other hand, the number of workers over the age of 65 is relatively small; it was approximately 3% of the total workforce in 2001 (U.S. Bureau of the Census, 2002).

The coefficient used in the health impact function is a weighted average of the coefficients in Ostro (1987, Table 3) using the inverse of the variance as the weight:

$$\beta = \frac{\sum_{i=1976}^{1981} \frac{\beta_i}{\sigma_{\beta_i}^2}}{\sum_{i=1976}^{1981} \frac{1}{\sigma_{\beta_i}^2}} = 0.0046$$

The standard error of the coefficient is calculated as follows, assuming that the estimated year-specific coefficients are independent:

$$\sigma_{\beta}^2 = Var\left(\frac{\sum_{i=1976}^{1981} \frac{\beta_i}{\sigma_{\beta_i}^2}}{\sum_{i=1976}^{1981} \frac{1}{\sigma_{\beta_i}^2}}\right) = Var\left(\frac{\sum_{i=1976}^{1981} \frac{\beta_i}{\sigma_{\beta_i}^2}}{\gamma}\right) = \sum_{i=1976}^{1981} Var\left(\frac{\beta_i}{\gamma \cdot \sigma_{\beta_i}^2}\right)$$

This eventually reduces down to:

$$\sigma_{\beta} = \sqrt{1/\gamma} = 0.00036$$

Functional Form: Log-linear

Coefficient: 0.0046

Standard Error: 0.00036

Incidence Rate: daily work-loss-day incidence rate per person ages 18 to 64 = 0.00595 (Adams, Hendershot, & Marano, 1999, Table 41; U.S. Bureau of the Census, 1997, No. 22)

Population: adult population ages 18 to 64

¹² The study used a two-week average pollution concentration; the health impact function uses a daily average, which is assumed to be a reasonable approximation.

Asthma-Related Effects

We pool the results of studies by Ostro et al. (2001) and Mar et al. (2004) to get an estimate of asthma exacerbation in asthmatics. In addition to the lower respiratory estimate, we include an upper respiratory estimate based on a study by Pope et al. (1991).

Exhibit C-9. Health Impact Functions for Particulate Matter and Asthma-Related Effects

Endpoint Name	Author	Year	Location	Age	Metric	Beta	Std Error	Functional Form
Asthma Exacerbation, Cough	Ostro et al.	2001	Los Angeles, CA	6-18	24-hr avg	0.000985	0.000747	Logistic
Asthma Exacerbation, Shortness of Breath	Ostro et al.	2001	Los Angeles, CA	6-18	24-hr avg	0.002565	0.001335	Logistic
Asthma Exacerbation, Wheeze	Ostro et al.	2001	Los Angeles, CA	6-18	24-hr avg	0.001942	0.000803	Logistic
Asthma Exacerbation, Cough	Mar et al.	2004	Vancouver, CAN	6-18	24-hr avg	0.01906	0.009828	Logistic
Asthma Exacerbation, Shortness of Breath	Mar et al.	2004	Vancouver, CAN	6-18	24-hr avg	0.01222	0.013849	Logistic
Upper Respiratory Symptoms	Pope et al.	1991	Utah Valley	9-11	24-hr avg	0.0036	0.0015	Logistic

Pooling Ostro et al. (2001) and Mar et al. (2004)

To characterize asthma exacerbations in children, we use two studies that followed panels of asthmatic children. Ostro et al. (2001) followed a group of 138 African-American children in Los Angeles for 13 weeks, recording daily occurrences of respiratory symptoms associated with asthma exacerbations (e.g., shortness of breath, wheeze, and cough). This study found a statistically significant association between $PM_{2.5}$, measured as a 12-hour average, and the daily prevalence of shortness of breath and wheeze endpoints. Although the association was not statistically significant for cough, the results were still positive and close to significance; consequently, we decided to include this endpoint, along with shortness of breath and wheeze, in generating incidence estimates.

Mar et al. (2004) followed nine asthmatic children for over eight months in Spokane, Washington. Data on respiratory symptoms and medication use were recorded daily by the study's subjects, while air pollution data was collected by the local air agency and Washington State University. The authors found a strong association between cough symptoms and several metrics of particulate matter, including $PM_{2.5}$.

We employed the following pooling approach in combining effect estimates from the two studies to produce a single asthma exacerbation incidence estimate. First, we pooled (with a

fixed/random effects approach) the incidence estimates based on the two studies for “cough” and “shortness of breath” separately. We then assigned an equal weight (i.e., 0.33) to the pooled results for cough, the pooled results for shortness of breath, and the (un-pooled) results for wheeze (from Ostro et al., 2001).

To prevent double-counting, we followed U.S. EPA (2005, p. 4-38) and focused the estimation on asthma exacerbations occurring in children and excluded adults from the calculation. Asthma exacerbations occurring in adults are assumed to be captured in the general population endpoints such as work loss days and MRADs. Consequently, if we had included an adult-specific asthma exacerbation estimate, this would likely have double-counted incidence for this endpoint. However, because the general population endpoints do not cover children (with regard to asthmatic effects), an analysis focused specifically on asthma exacerbations for children (6 to 18 years of age) could be conducted without concern for double-counting.

Asthma Exacerbation: Cough, Wheeze, and Shortness of Breath (Ostro et al., 2001)

Ostro et al. (2001) studied the relation between air pollution in Los Angeles and asthma exacerbation in African-American children (8 to 13 years old) from August to November 1993. They used air quality data for PM₁₀, PM_{2.5}, NO₂, and O₃ in a logistic regression model with control for age, income, time trends, and temperature-related weather effects.¹³ Asthma symptom endpoints were defined in two ways: “probability of a day with symptoms” and “onset of symptom episodes”. New onset of a symptom episode was defined as a day with symptoms followed by a symptom-free day. The authors found cough prevalence associated with PM₁₀ and PM_{2.5} and cough incidence associated with PM_{2.5}, PM₁₀, and NO₂. Ozone was not significantly associated with cough among asthmatics.

Note that the study focused on African-American children ages 8 to 13 years old. We apply the function based on this study to the general population ages 6 to 18 years old.

Asthma Exacerbation, Cough

The coefficient and standard error are based on an odds ratio of 1.03 (95% CI 0.98-1.07) for a 30 µg/m³ increase in 12-hour average PM_{2.5} concentration (Ostro et al., 2001, Table 4, p. 204).

Functional Form: Logistic

Coefficient: 0.000985

Standard Error: 0.000747

Incidence Rate: daily cough rate per person (Ostro et al., 2001, p. 202) = 0.145

Population: Asthmatic population ages 6 to 18 = 10.70%.¹⁴

¹³ The authors note that there were 26 days in which PM_{2.5} concentrations were reported higher than PM₁₀ concentrations. The majority of results the authors reported were based on the full dataset. These results were used for the basis for the C-R functions.

¹⁴ The American Lung Association (2010, Table 7) estimates asthma prevalence for children 5-17 at 10.70% (based on data from the 2008 National Health Interview Survey).

Asthma Exacerbation, Shortness of Breath

The coefficient and standard error are based on an odds ratio of 1.08 (95% CI 1.00-1.17) for a 30 $\mu\text{g}/\text{m}^3$ increase in 12-hour average $\text{PM}_{2.5}$ concentration (Ostro et al., 2001, Table 4, p. 204).

Functional Form: Logistic

Coefficient: 0.002565

Standard Error: 0.001335

Incidence Rate: daily shortness of breath rate per person (Ostro et al., 2001, p. 202) = 0.074

Population: Asthmatic population ages 6 to 18 = 10.70%.

Asthma Exacerbation, Wheeze

The coefficient and standard error are based on an odds ratio of 1.06 (95% CI 1.01-1.11) for a 30 $\mu\text{g}/\text{m}^3$ increase in 12-hour average $\text{PM}_{2.5}$ concentration (Ostro et al., 2001, Table 4, p. 204).

Functional Form: Logistic

Coefficient: 0.001942

Standard Error: 0.000803

Incidence Rate: daily wheeze rate per person (Ostro et al., 2001, p. 202) = 0.173

Population: Asthmatic population ages 6 to 18 = 10.70%.

Asthma Exacerbation, Cough and Shortness of Breath (Mar et al., 2004)

Mar et al. (2004) studied the effects of various size fractions of particulate matter on respiratory symptoms of adults and children with asthma, monitored over many months. The study was conducted in Spokane, Washington, a semiarid city with diverse sources of particulate matter. Data on respiratory symptoms and medication use were recorded daily by the study's subjects, while air pollution data was collected by the local air agency and Washington State University. Subjects in the study consisted of 16 adults – the majority of whom participated for over a year – and nine children, all of whom were studied for over eight months. Among the children, the authors found a strong association between cough symptoms and several metrics of particulate matter, including $\text{PM}_{2.5}$. However, the authors found no association between respiratory symptoms and $\text{PM}_{2.5}$ of any metric in adults. Mar et al. therefore concluded that the discrepancy in results between children and adults was due either to the way in which air quality was monitored, or a greater sensitivity of children than adults to increased levels of $\text{PM}_{2.5}$ air pollution.

Asthma Exacerbation, Cough

In a single-pollutant model, the coefficient and standard error are estimated from the odds ratio (1.21) and 95% confidence interval (1.00-1.47) for a 10.0 $\mu\text{g}/\text{m}^3$ increase in 1-day lagged concentration of $\text{PM}_{2.5}$ (Mar et al., 2004, Table 7).

Functional Form: Logistic

Coefficient: 0.019062

Standard Error: 0.009828

Incidence Rate: daily cough rate per person (Ostro et al., 2001) = 14.5%

Population: The study reported results for population ages 7-12. For comparability to other studies, we apply the results to the population of ages 6 to 18. Asthmatic population ages 6 to 18 = 10.70%.¹⁵

Asthma Exacerbation, Shortness of Breath

In a single-pollutant model, the coefficient and standard error are estimated from the odds ratio (1.13) and 95% confidence interval (0.86-1.48) for a 10.0 µg/m³ increase in current-day concentration of PM_{2.5} (Mar et al., 2004, Table 7).

Functional Form: Logistic

Coefficient: 0.012222

Standard Error: 0.013849

Incidence Rate: daily shortness of breath rate per person (Ostro et al., 2001, p.202) = 7.4%

Population: The study reported results for population ages 7-12. For comparability to other studies, we apply the results to the population of ages 6 to 18. Asthmatic population ages 6 to 18 = 10.70%.

Upper Respiratory Symptoms (Pope, 1991)

Using logistic regression, Pope et al. (1991) estimated the impact of PM₁₀ on the incidence of a variety of minor symptoms in 55 subjects (34 “school-based” and 21 “patient-based”) living in the Utah Valley from December 1989 through March 1990. The children in the Pope et al. study were asked to record respiratory symptoms in a daily diary. With this information, the daily occurrences of upper respiratory symptoms (URS) and lower respiratory symptoms (LRS) were related to daily PM₁₀ concentrations. Pope et al. describe URS as consisting of one or more of the following symptoms: runny or stuffy nose; wet cough; and burning, aching, or red eyes.

Levels of ozone, NO₂, and SO₂ were reported low during this period, and were not included in the analysis. The sample in this study is relatively small and is most representative of the asthmatic population, rather than the general population. The school-based subjects (ranging in age from 9 to 11) were chosen based on “a positive response to one or more of three questions: ever wheezed without a cold, wheezed for 3 days or more out of the week for a month or longer, and/or had a doctor say the ‘child has asthma’ (Pope, 1991, p. 669).” The patient-based subjects (ranging in age from 8 to 72) were receiving treatment for asthma and were referred by local physicians. Regression results for the school-based sample (Pope, 1991, Table 5) show PM₁₀ significantly associated with both upper and lower respiratory symptoms. The patient-based sample did not find a significant PM₁₀ effect. The results from the school-based sample are used here.

¹⁵ The American Lung Association (2010, Table 7) estimates asthma prevalence for children 5-17 at 10.70% (based on data from the 2008 National Health Interview Survey).

The coefficient and standard error for a one $\mu\text{g}/\text{m}^3$ change in PM_{10} is reported in Table 5.

Functional Form: Logistic

Coefficient: 0.0036

Standard Error: 0.0015

Incidence Rate: daily upper respiratory symptom incidence rate per person = 0.3419 (Pope, 1991, Table 2)

Population: Asthmatic population ages 6 to 18 = 10.70%¹⁶ of population ages 9 to 11.

¹⁶ The American Lung Association (2010, Table 7) estimates asthma prevalence for children 5-17 at 10.70% (based on data from the 2008 National Health Interview Survey).

Appendix D: Baseline Incidence Rates for Adverse Health Effects

Health impact functions developed from log-linear or logistic models estimate the percent change in an adverse health effect associated with a given pollutant change. In order to estimate the absolute change in incidence using these functions, we need the baseline incidence rate of the adverse health effect. For certain health effects, such as asthma exacerbation, we need a prevalence rate, which estimates the percentage of the general population with a given ailment like asthma. This appendix describes the data used to estimate baseline incidence rates and prevalence rates for the health effects considered in this analysis.

Mortality

This section describes the development of county mortality rates for year 2020 for use in COBRA.¹ First, we describe the source of 2004-2006 individual-level mortality data and the calculation of county-level mortality rates. Then we describe how we use national-level Census mortality rate projections to develop county-level mortality rate projections for year 2020.

Mortality Data for 2004-2006

We obtained individual-level mortality data from 2004-2006 for the whole United States from the Centers for Disease Control (CDC), National Center for Health Statistics (NCHS). The data were compressed into a CD-ROM, which contains death information for each decedent, including residence county FIPS, age at death, month of death, and underlying causes (ICD-10 codes).

Using the detailed mortality data combined with county-level inter-censal population estimates,² we generated age-, cause-, and county-specific mortality rates using the following formula:

$$R_{i,j,k} = \frac{D_{i,j,k}(2004) + D_{i,j,k}(2005) + D_{i,j,k}(2006)}{P_{i,k}(2004) + P_{i,k}(2005) + P_{i,k}(2006)}$$

where $R_{i,j,k}$ is the mortality rate for age group i , cause j , and county k ; D is the death count; and P is the population.

Following CDC Wonder (<http://wonder.cdc.gov>), we treated mortality rates as “unreliable” when the death count is less than 20.³ For each combination of age group and mortality cause, we used the following procedure to deal with the problem of “unreliable” rates:

¹ We use projected 2020 mortality rates for year 2017 in COBRA.

² The detailed mortality data obtained from CDC do not include population. The county-level inter-censal population estimates are based on US Census of Population and Housing 2010 and forecasts developed by Woods & Poole (2011).

- For a given state, we grouped the counties where the death count (i.e., the numerator on the right-hand side of the above equation) was less than 20 and summed those death counts across those counties. If the sum of deaths was greater than or equal to 20, we then summed the populations in those counties, and calculated a single rate for the “state collection of counties” by dividing the sum of deaths by the sum of populations in those counties. This rate was then applied to each of those counties.⁴
- If the sum of deaths calculated in the above step was still less than 20, the counties in the “state collection of counties” were not assigned the single rate from the above step. Instead, we proceeded to the regional level (see Exhibit D-1 for region definition). In each region, we identified all counties whose death counts were less than 20 (excluding any such counties that were assigned a rate in the previous step). We summed the death counts in those counties. If the sum of deaths was greater than or equal to 20, we then summed the populations in those counties, and calculated a single rate for the “regional collection of counties” by dividing the sum of deaths by the sum of populations in those counties. This rate was then applied to each of those counties in the “regional collection of counties.”⁵

Exhibit D-1. Regional Definitions from U.S. Census

Region	States Included
Northeast	Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, Connecticut, New York, New Jersey, Pennsylvania
Midwest	Ohio, Indiana, Illinois, Michigan, Wisconsin, Minnesota, Iowa, Missouri, North Dakota, South Dakota, Nebraska, Kansas
South	Delaware, Maryland, District of Columbia, Virginia, West Virginia, North Carolina, South Carolina, Georgia, Florida, Kentucky, Tennessee, Alabama, Mississippi, Arkansas, Louisiana, Oklahoma, Texas
West	Montana, Idaho, Wyoming, Colorado, New Mexico, Arizona, Utah, Nevada, Washington, Oregon, California, Alaska, Hawaii

- If the sum of deaths calculated in the previous (regional) step was still less than 20, the counties in the “regional collection of counties” were not assigned the single rate from the above step. Instead, we proceeded to the national level, identifying all counties in the nation whose death counts were less than 20 (excluding any such counties that were assigned a rate in the previous steps). We summed the death counts in those counties and

³ Among all the calculated age-, cause-, and county-specific mortality rates, there were about 67% “unreliable” rates.

⁴ After this adjustment, there were 17% unreliable rates left.

⁵ After this regional adjustment, there were 7% unreliable rates left.

divided by the sum of the populations in those counties to derive a single rate for the “national collection of counties.” This rate was then applied to each of those counties in the “national collection of counties.”⁶

Exhibit D-2 shows the resulting national average all-cause mortality rates.

Exhibit D-2. National All-Cause Mortality Rates (per 100 people per year) by Age Group

Mortality Category	Infant *	1--17	18-- 24	25-- 34	35-- 44	45-- 54	55-- 64	65-- 74	75-- 84	85+
Mortality, All Cause	0.241	0.028	0.089	0.106	0.194	0.430	0.902	2.126	5.234	14.654

* We estimate post-neonatal mortality (deaths after the first month) for infants because the health impact function (see Appendix F) estimates post-neonatal mortality.

Mortality Rate Projections to 2020

To estimate age- and county-specific mortality rates in year 2020, we calculated adjustment factors, based on a series of Census Bureau projected national mortality rates (for all-cause mortality), to adjust the age- and county-specific mortality rates calculated using 2004-2006 data as described above. We used the following procedure:

- For each age group, we obtained the series of projected national mortality rates from 2005 to 2050 (see the 2005 rate in Exhibit D-3) based on Census Bureau projected life tables.⁷
- We then calculated, separately for each age group, the ratio of Census Bureau national mortality rate in year 2020 to the 2005 rate. These ratios are shown in Exhibit D-4.
- Finally, to estimate mortality rates in year 2020 that are both age group-specific and county-specific, we multiplied the county- and age-group-specific mortality rates for 2004-2006 by the appropriate ratio calculated in the previous step. For example, to estimate the projected mortality rate in 2020 among ages 18-24 in Wayne County, MI, we multiplied the mortality rate for ages 18-24 in Wayne County in 2004-2006 by the ratio of Census Bureau projected national mortality rate in 2020 for ages 18-24 to Census Bureau national mortality rate in 2005 for ages 18-24.

⁶ Even after this national adjustment, there were about 1% unreliable rates left. In these cases, we simply calculated a single rate for the “national collection of counties, even though it was “unreliable,” and assigned it to those counties in the “national collection of counties.”

⁷ For a detailed description of the model, the assumptions, and the data used to create Census Bureau projections, see the working paper, "Methodology and Assumptions for the Population Projections of the United States: 1999 to 2100, Working Paper #38.", which is available on <http://www.census.gov/population/www/documentation/twps0038/twps0038.html> (Hollman, et al. 2000) .

Exhibit D-3. All-Cause Mortality Rate (per 100 people per year), by Source, Year, and Age Group

Source & Year	Infant*	1--17	18--24	25--34	35--44	45--54	55--64	65--74	75--84	85+
Calculated CDC 2004-2006	0.684/0.241	0.028	0.089	0.106	0.194	0.430	0.902	2.126	5.234	14.654
Census Bureau 2005	0.654	0.029	0.088	0.102	0.183	0.387	0.930	2.292	5.409	13.091

* The Census Bureau estimate is for all deaths in the first year of life. COBRA uses post-neonatal mortality (deaths after the first month, i.e., 0.23 per 100 people) because the health impact function (see Appendix F) estimates postneonatal mortality. For comparison purpose, we also calculated the rate for all deaths in the first year, which is 0.684 per 100 people).

Exhibit D-4. Ratio of 2020 All-Cause Mortality Rate to 2005 Estimated All-Cause Mortality Rate, by Age Group

Year	Infant	1--17	18--24	25--34	35--44	45--54	55--64	65--74	75--84	85+
2020	0.85	0.81	0.86	0.90	0.83	0.85	0.87	0.85	0.83	0.91

Hospitalizations

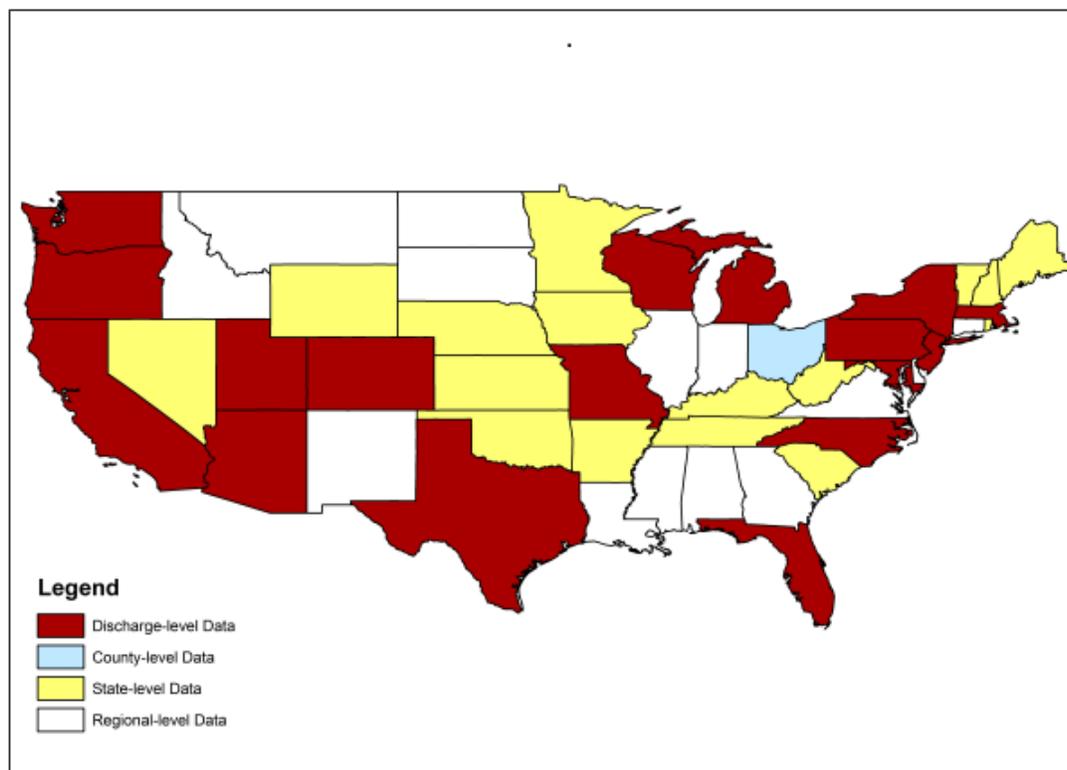
Hospitalization rates were calculated using data from the Healthcare Cost and Utilization Project (HCUP). HCUP is a family of health care databases developed through a Federal-State-Industry partnership and sponsored by the Agency for Healthcare Research and Quality (AHRQ).⁸ HCUP products include the State Inpatient Databases (SID), the State Emergency Department Databases (SEDD), the Nationwide Inpatient Sample (NIS), and the Nationwide Emergency Department Sample (NEDS). HCUP databases can be obtained from the following data services:

- The HCUP Central Distributor: Many of the HCUP databases are available for purchase through the HCUP Central Distributor. The databases include detailed information for individual discharges, such as primary diagnosis (in ICD-9 codes), patient's age and residence county.
- HCUP State Partners: Some HCUP participating states do not release their data to the Central Distributor; however, the data may be obtained through contacting the State Partners. Some State Partners (e.g., CA, TX, and NY) provided discharge-level data; others (e.g., OH) provided summarized data.
- HCUPnet: This is a free, on-line query system based on data from HCUP. It provides access to summary statistics at the state, regional and national levels.

Exhibit D-5 shows the level of hospitalization data (e.g, discharge-level or state-level) for each state. Note that for some states neither discharge-level nor state-level data were available. In such cases we used regional statistics from HCUPnet to estimate hospitalization rates for those states.

⁸ More information about HCUP can be found at <http://www.hcup-us.ahrq.gov/>.

Exhibit D-5. Hospitalization Data from HCUP



The procedures for calculating hospitalization rates are summarized as follows:⁹

- For states with discharge-level data:
 - We calculated age-, health endpoint-, and county-specific hospitalization counts.¹⁰
 - The above calculation excluded hospitalizations with missing patient age or county FIPS, which may lead to underestimation of rates. Therefore we scaled up the previously calculated age-, endpoint-, and county-specific counts using an adjustment factor obtained as follows:
 - We first counted the number of discharges for a specific endpoint in the state **including** those discharges with missing age or county FIPS.
 - We then counted the number of discharges for the endpoint in the state **excluding** those records with missing age or county FIPS.
 - The adjustment factor is the ratio of the two counts.

⁹ The data year for most states is 2007; the exception is MA, for which the data year is 2006. We assume hospitalization rates are reasonably constant from 2006–2007 and consider all as 2007 rates.

¹⁰ Ohio was the only state that, while not providing discharge-level data, did provide county-level data for each age group-endpoint combination.

- We calculated hospitalization rates for each county by dividing the adjusted county-level hospitalization counts by the Census estimated county-level population for the corresponding year (2006 or 2007). Following CDC Wonder, we treated rates as “unreliable” when the hospitalization count was less than 20, using the same procedure we used for mortality rates above.
- For states with summarized state statistics (from HCUPnet) we calculated the state-, age-, endpoint- specific hospitalization rates and applied them to each county in the state. We used the previously described procedure to adjust the “unreliable” rates.
- For states without discharge-level or state-level data:
 - We obtained the endpoint-specific hospitalization counts in each region from HCUPnet/NIS (we refer to this count for the i th endpoint in the j th region as “ $TOTAL_{ij}$ ”).
 - For those states in the j th region that do have discharge-level or state-level data, we summed the hospital admissions by endpoint (we refer to this count for the i th endpoint in the j th region as “ SUB_{ij} ”).
 - We then estimated the hospitalization count for states without discharge or state data for the i th endpoint in the j th region as $TOTAL_{ij} - SUB_{ij}$. Note that while this count is endpoint- and region- specific, it is not age-specific. We obtained the distribution of hospital admission counts across age groups based on the National Hospital Discharge Survey (NHDS) and assumed the same distribution for the HCUP hospitalizations. We then applied this distribution to the estimated hospital counts (i.e., $TOTAL_{ij} - SUB_{ij}$) to obtain endpoint-, region-, and age-specific counts.
 - Using the corresponding age- and region-specific populations, we calculated age-specific hospitalization rates for the i th endpoint in the j th region and applied them to those counties in the region that didn’t have discharge-level or state-level data.

Exhibit D-6 shows the resulting average national hospitalization rates by health endpoint and age group.

- The SEDD databases include only those ER visits that ended with discharge. To identify the ER visits that ended in hospitalization, we used a variable called “admission source” in the SID databases. Admission source identified as “emergency room” indicates that the hospital admission came from the ER – i.e., the ER visit ended in hospitalization. For each combination of age group, endpoint and county, we summed the ER visits that ended with discharge and those that resulted in hospitalization.
- The data year varies across the states from 2005 to 2007 (see Exhibit D-7); we assumed that ER visit rates are reasonably constant across these three years and consider them as 2006 rates.
- Instead of using HCUPnet/NIS and NHDS in the last step as described for hospitalizations, we used HCUPnet/NEDS and the National Ambulatory Medical Care Survey (NAMCS) to calculate ER visit rates for states without discharge level or state level data.

Exhibit D-8 shows the resulting average national rates of asthma emergency room visits by age group.

Exhibit D-8. National Emergency Room Visit Rates for Asthma, by Age Group

ER Category	ICD-9 Codes	ER Visit Rate (visits per 100 people per year)				
		0-17	18-44	45-64	65-84	85+
asthma	493	0.860	0.573	0.393	0.248	0.308

Nonfatal Heart Attacks

The relationship between short-term particulate matter exposure and heart attacks was quantified in case-crossover analyses by Peters et al (2001), Pope et al. (2006), and Sullivan et al. (2005). The study population was selected from heart attack survivors in a medical clinic. Therefore, the applicable population to apply to the C-R function is all individuals surviving a heart attack in a given year. Several data sources are available to estimate the number of heart attacks per year. For example, several cohort studies have reported estimates of heart attack incidence rates in the specific populations under study. However, these rates depend on the specific characteristics of the populations under study and may not be the best data to extrapolate nationally.

An alternative approach to the estimation of heart attack rates is to use data from the HCUP, assuming that all heart attacks that are not instantly fatal will result in a hospitalization. According to the HCUPnet, in 2009 there were approximately 633,356 hospitalizations due to

heart attacks (acute myocardial infarction: ICD-9 code of 410, primary diagnosis).¹¹ We used county-level hospitalization rates over estimates extrapolated from cohort studies because the former is part of a nationally representative survey with a larger sample size, which is intended to provide reliable national estimates. The hospitalization section above describes the detailed procedure for developing the incidence rates for hospitalization of AMI. As additional information is provided regarding the American Heart Association methodology, we will evaluate the usefulness of this estimate of heart attack incidence.

Rosamond et al. (1999) reported that approximately six percent of male and eight percent of female hospitalized heart attack patients die within 28 days (either in or outside of the hospital). We, therefore, applied a factor of 0.93 to the count of hospitalizations to estimate the number of nonfatal heart attacks per year. Note that we did not adjust for fatal AMIs in the incidence rate estimation, due to the way that the epidemiological studies are designed. Those studies consider total admissions for AMIs, which includes individuals living at the time the studies were conducted. Therefore, we use the definition of AMI that matches the definition in the epidemiological studies.

Exhibit D-9 presents the national nonfatal heart attack incidence rates around year 2007 by age group (Note: county-level rates around year 2007 are used in COBRA).

Exhibit D-9. Nonfatal Heart Attack Rates by Age Group

Endpoint	Nonfatal Heart Rate by Age Group (admissions per 100 people per year)*				
	0-17	18-44	45-64	65-84	85+
Nonfatal heart attack	0.000	0.033	0.259	0.767	1.78

* Rates are based on data from the 2007 HCUP/SID.

Other Acute Effects

For many of the minor effect studies, baseline rates from a single study are often the only source of information, and we assume that these rates hold for locations in the U.S. The use of study-specific estimates is likely to increase the uncertainty around the estimate because they are often estimated from a single location using a relatively small sample. These endpoints include: acute bronchitis, upper respiratory symptoms, and lower respiratory symptoms. Exhibit D-10 presents a summary of these baseline rates.

¹¹ Source: Online query on HCUPnet website (AHRQ 2012), accessed 1-13-2012
<http://hcupnet.ahrq.gov/HCUPnet.app/HCUPnet.jsp?Id=53F290DC050F1296&Form=SelLAY&GoTo=MAINSEL&JS=Y>

Exhibit D-10. Selected Acute Effects Rates

Endpoint	Age	Parameter	Rate	Source
Acute Bronchitis	8-12	Incidence	4.300	(American Lung Association, 2002, Table 11)
Lower Respiratory Symptoms (LRS)	7-14	Incidence	43.8	(Schwartz et al., 1994, Table 2)
Minor Restricted Activity Days (MRAD)	18-64	Incidence	780.0	(Ostro & Rothschild, 1989, p. 243)
Work Loss Day (WLD)	18-64	Incidence	217.2	(Adams, Hendershot, & Marano, 1999, Table 41; U.S. Bureau of the Census, 1997)

Acute Bronchitis

The annual rate of acute bronchitis for children ages 5 to 17 was obtained from the American Lung Association (2002). The authors reported an annual incidence rate per person of 0.043, derived from the 1996 National Health Interview Survey.

Lower Respiratory Symptoms

Lower respiratory symptoms (LRS) are defined as two or more of the following: cough, chest pain, phlegm, and wheeze. The proposed yearly incidence rate for 100 people, 43.8, is based on the percentiles in Schwartz et al (1994, Table 2). The authors did not report the mean incidence rate, but rather reported various percentiles from the incidence rate distribution. The percentiles and associated per person per day values are 10th = 0 percent, 25th = 0 percent, 50th = 0 percent, 75th = 0.29 percent, and 90th = 0.34 percent. The most conservative estimate consistent with the data are to assume the incidence per person per day is zero up to the 75th percentile, a constant 0.29 percent between the 75th and 90th percentiles, and a constant 0.34 percent between the 90th and 100th percentiles. Alternatively, assuming a linear slope between the 50th and 75th, 75th and 90th, and 90th to 100th percentiles, the estimated mean incidence rate per person per day is 0.12 percent.¹² We used the latter approach in this analysis, and then multiplied by 100 and by 365 to calculate the incidence rate per 100 people per year.

Minor Restricted Activity Days (MRAD)

Ostro and Rothschild (1989, p. 243) provide an estimate of the annual incidence rate of MRADs (7.8). We multiplied this estimate by 100 to get an annual rate per 100 people.

Work Loss Days

The yearly work-loss-day incidence rate per 100 people is based on estimates from the 1996 National Health Interview Survey (Adams et al., 1999, Table 41). They reported a total annual work loss days of 352 million for individuals ages 18 to 65. The total population of individuals of this age group in 1996 (162 million) was obtained from (U.S. Bureau of the Census, 1997).

¹² For example, the 62.5th percentile would have an estimated incidence rate per person per day of 0.145 percent.

The average annual rate of work loss days per individual (2.17) was multiplied by 100 to obtain the average yearly work-loss-day rate of 217 per 100 people.

Asthma-Related Health Effects

Several studies have examined the impact of air pollution on asthma development or exacerbation in the asthmatic population. Many of the baseline incidence rates used in the C-R functions are based on study-specific estimates. The baseline rates for the various endpoints are described below and summarized in Exhibit D-11.

Exhibit D-11. Asthma-Related Health Effects Rates

Endpoint	Age	Parameter ^a	Rate	Source
Asthma Exacerbation, Cough	6-18	Incidence	24.46	
		Prevalence	14.50%	
Asthma Exacerbation, Shortness of Breath	6-18	Incidence	13.51	(Ostro, Lipsett, Mann, Braxton-Owens, & White, 2001, p. 202) ^b
		Prevalence	7.40%	
Asthma Exacerbation, Wheeze	6-18	Incidence	27.74	
		Prevalence	17.3%	
Asthma	6-18	Prevalence	10.70%	(American Lung Association, 2010,, Table 7) ^c
Upper Respiratory Symptoms (URS)	9-11	Incidence	124.79	(Pope, Dockery, Spengler, & Raizenne, 1991, Table 2)

^a The incidence rate is the number of cases per person per year. Prevalence refers to the fraction of people that have a particular illness during a particular time period.

^b the rates in the study were for African American children of ages 8-13. We apply it to children aged 6-18 to match what was used in the selected epidemiological studies.

^c The American Lung Association (2010, Table 7) estimates asthma prevalence for children 5- 17 at 10.70% (based on data from the 2008 National Health Interview Survey). We apply to ages 6-18 because what was used in the selected epidemiological studies.

Appendix E: Population Forecasts

To estimate the change in population exposure to air pollution, we use projections based on US Census of Population and Housing 2010 and forecasting models developed by Woods & Poole (2011). The Woods and Poole (WP) database contains county-level projections of population by age, sex, ethnicity, and race out to 2040. Projections in each county are determined simultaneously with every other county in the United States to take into account patterns of economic growth and migration. The sum of growth in county-level populations is constrained to equal a previously determined national population growth, based on Bureau of Census estimates. The projection year used for COBRA is 2017.

According to WP, linking county-level growth projections together and constraining to a national-level total growth avoids potential errors introduced by forecasting each county independently. County projections are developed in a four-stage process. First, national-level variables such as income, employment, and populations are forecasted. Second, employment projections are made for 172 economic areas defined by the Bureau of Economic Analysis, using an “export-base” approach, which relies on linking industrial sector production of non-locally consumed production items, such as outputs from mining, agriculture, and manufacturing with the national economy. The export-based approach requires estimation of demand equations or calculation of historical growth rates for output and employment by sector. Third, population is projected for each economic area based on net migration rates derived from employment opportunities and following a cohort component method based on fertility and mortality in each area. Fourth, employment and population projections are repeated for counties, using the economic region totals as bounds. The age, sex, ethnicity, and race distributions for each region or county are determined by aging the population by single year of age by sex and race for each year through 2040 based on historical rates of mortality, fertility, and migration.

Appendix F: Economic Value of Health Effects

This appendix presents the mean estimate of the unit values used in this analysis. Exhibit F-1 lists these unit values.

Exhibit F-1. Unit Values for Economic Valuation of Health Endpoints (2010 \$)

Health Endpoint	Age Range	Unit Value (2017 Income Level)	
		3% DR	7% DR
Mortality ^a	25 - 99	\$8,434,924	\$7,512,853
Infant Mortality ^b	0 - 0	\$9,401,680	\$9,401,680
Acute Myocardial Infarction, Nonfatal ^c	0 - 24	\$33,259	\$31,446
Acute Myocardial Infarction, Nonfatal ^c	25 - 44	\$45,085	\$42,033
Acute Myocardial Infarction, Nonfatal ^c	45 - 54	\$50,689	\$47,050
Acute Myocardial Infarction, Nonfatal ^c	55 - 64	\$134,003	\$121,641
Acute Myocardial Infarction, Nonfatal ^c	65 - 99	\$33,259	\$31,446
Acute Myocardial Infarction, Nonfatal ^d	0 - 24	\$163,051	\$163,051
Acute Myocardial Infarction, Nonfatal ^d	25 - 44	\$174,876	\$173,638
Acute Myocardial Infarction, Nonfatal ^d	45 - 54	\$180,480	\$178,655
Acute Myocardial Infarction, Nonfatal ^d	55 - 64	\$263,795	\$253,247
Acute Myocardial Infarction, Nonfatal ^d	65 - 99	\$163,051	\$163,051
HA, All Cardiovascular (less AMI)	18 - 64	\$41,002	\$41,002
HA, All Cardiovascular (less AMI)	65 - 99	\$38,618	\$38,618
HA, All Respiratory	65 - 99	\$32,697	\$32,697
HA, Asthma	0 - 17	\$15,430	\$15,430
HA, Chronic Lung Disease	18-64	\$20,349	\$20,349
Asthma ER Visits (Smith et al. (1997))	0 - 99	\$464	\$464
Asthma ER Visits (Stanford et al. (1999))	0 - 99	\$388	\$388
Acute Bronchitis	8 - 12	\$477	\$477
Lower Resp. Symptoms	7 - 14	\$21	\$21
Upper Resp. Symptoms	9 - 11	\$33	\$33
MRAD	18 - 64	\$68	\$68
Work Loss Days	18 - 64	\$160	\$160
Asthma Exacerbation (Cough, Shortness of Breath, or Wheeze)	6 - 18	\$57	\$57

NOTE: ^a Mortality value after adjustment for 20-year lag.

^b Infant mortality value is not adjusted for 20-year lag.

^c Based on Russell (1998)

^d Based on Wittels (1990)

Selecting Unit Values for Monetizing Health Endpoints

The appropriate economic value for a change in a health effect depends on whether the health effect is viewed ex ante (before the effect has occurred) or ex post (after the effect has occurred). Reductions in ambient concentrations of air pollution generally lower the risk of future adverse health effects by a small amount for a large population. The appropriate economic measure is therefore ex ante WTP for changes in risk. However, epidemiological studies generally provide estimates of the relative risks of a particular health effect avoided due to a reduction in air pollution. A convenient way to use this data in a consistent framework is to convert probabilities

to units of avoided statistical incidences. This measure is calculated by dividing individual WTP for a risk reduction by the related observed change in risk.

For example, suppose a measure is able to reduce the risk of premature mortality from 2 in 10,000 to 1 in 10,000 (a reduction of 1 in 10,000). If individual WTP for this risk reduction is \$100, then the WTP for an avoided statistical premature mortality amounts to \$1 million (\$100/0.0001 change in risk). Using this approach, the size of the affected population is automatically taken into account by the number of incidences predicted by epidemiological studies applied to the relevant population. The same type of calculation can produce values for statistical incidences of other health endpoints.

For some health effects, such as hospital admissions, WTP estimates are generally not available. In these cases, we use the cost of treating or mitigating the effect. For example, for the valuation of hospital admissions EPA used the avoided medical costs as an estimate of the value of avoiding the health effects causing the admission. These COI estimates generally understate the true value of reductions in risk of a health effect, because, while they reflect the direct expenditures related to treatment, they omit the value of avoiding the pain and suffering from the health effect itself.

Updating Values for Inflation

The studies based on which the unit values were developed report estimates for a range for years prior to 2010. To allow for the effect of inflation, we have adjusted these values to reflect prices in 2010\$. Because some functions are based on willingness to pay to avoid illness, while others are based on cost of illness and/or lost wages, three different inflation indices are used. These are the All Goods Index, the Medical Cost Index, and the Wage Index, respectively. Exhibit F-2 summarizes the types of inflation indices and their sources used to adjust different types of unit values in COBRA.

Exhibit F-2. Type of Inflation Index Used for Adjust Unit Values for Health Effects Endpoints

Index	Source	Health Effects Endpoints
All Goods Index	Bureau of Labor Statistics' (BLS) Consumer Price Index (CPI)	Acute Bronchitis Asthma Exacerbation Lower Respiratory Symptoms Mortality Minor Restricted Activity Days Upper Respiratory Symptoms
Medical Cost Index	BLS/CPI	Acute Myocardial Infarction Emergency Room Visits Hospital Admissions
Wage Index	BLS Employment Cost Index for private industry workers, 2001-2010	Acute Myocardial Infarction Hospital Admissions

Growth in Unit Values Reflecting Growth in National Income

The unit value estimates reflect expected growth in real income over time. This is consistent with economic theory, which argues that WTP for most goods (such as health risk reductions) will

increase if real incomes increase. There is substantial empirical evidence that the income elasticity of WTP for health risk reductions is positive, although there is uncertainty about its exact value (and it may vary by health effect). Although one might assume that the income elasticity of WTP is unit elastic (e.g., a 10 percent higher real income level implies a 10 percent higher WTP to reduce health risks), empirical evidence suggests that income elasticity is substantially less than one and thus relatively inelastic. As real income rises, the WTP value also rises but at a slower rate than real income.

The effects of real income changes on WTP estimates can influence benefits estimates in two ways: through real income growth between the year a WTP study was conducted and the year for which benefits are estimated, and through differences in income between study populations and the affected populations at a particular time. Following the analysis in the 2006 PM_{2.5} NAAQS regulatory impact assessment (U.S. EPA, 2006), we have focused on the former.

The income adjustment in COBRA follows the approach used by EPA (2005, p. 4-17), who adjusted the valuation of human health benefits upward to account for projected growth in real U.S. income. Faced with a dearth of estimates of income elasticities derived from time-series studies, EPA applied estimates derived from cross-sectional studies.¹ The available income elasticities suggest that the severity of a health effect is a primary determinant of the strength of the relationship between changes in real income and changes in WTP. As a result, EPA (2005, p. 4-18) used different elasticity estimates to adjust the WTP for minor health effects, severe and chronic health effects, and premature mortality (see Exhibit F-3).

Exhibit F-3. Elasticity Values Used to Account for National Income Growth

Benefit Category	Central Elasticity Estimate
Minor Health Effect	0.14
Severe & Chronic Health Effects	0.45
Premature Mortality	0.40

In addition to elasticity estimates, projections of populations and real gross domestic product (GDP) are needed to adjust benefits to reflect real per capita income growth. COBRA uses population and GDP projections developed by EPA, which are described in EPA (2005, p. 4-17). To estimate national population growth rates for the years between 1990 and 1999, EPA used national population estimates U.S. Census Bureau (Hollman, Mulder, & Kallan, 2000). These population estimates are based on an application of a cohort-component model to 1990 U.S. Census data projections (U.S. Bureau of the Census, 2000). For the years between 2000 and 2010, EPA applied growth rates based on the U.S. Census Bureau projections to the U.S. Census estimate of national population in 2000. EPA used projections of real GDP provided in Kleckner and Neumann (1999) for the years 1990 to 2010, and projections of real GDP (in chained 1996 dollars) provided by Standard and Poor's (2000) for the years 2010 to 2020.

¹ Details of the procedure can be found in Kleckner and Neumann 1999.

Using the method outlined in Kleckner and Neumann (1999) and the population and income data described above, EPA (2005, p. 4-18) calculated WTP adjustment factors for each of the elasticity estimates. Benefits for each of the categories (minor health effects, severe and chronic health effects, premature mortality, and visibility) are adjusted by multiplying the unadjusted benefits by the appropriate adjustment factor.

Note that because of a lack of data on the dependence of COI on income, and a lack of data on projected growth in average wages, no adjustments are made to benefits estimates based on the COI approach or to work loss days benefits estimates. This lack of adjustment would tend to result in an under-prediction of benefits in future years, because it is likely that increases in real U.S. income would also result in increased COI (due, for example, to increases in wages paid to medical workers) and increased cost of work loss days and lost worker productivity (reflecting that if worker incomes are higher, the losses resulting from reduced worker production would also be higher).

Valuation Pooling

In some cases there are multiple valuations available for a health effect, with no one valuation clearly superior to another. In such cases we pooled valuations in COBRA.

- Smith et al. (1997) and Stanford et al. (1999) both evaluate asthma ER visits using COI. We assign equal weight to each study (i.e., 0.5) and COBRA will then use the weighted average to value ER visit.
- To value Acute Myocardial Infarction, we pool Russell (1998) and Wittels (1990) by assigning equal weight (i.e., 0.5) to each.
- To value respiratory hospitalization, we sum across non-overlapping respiratory hospitalization effects, i.e., Asthma HA (age 0-17), Chronic Lung Disease HA (age 18-64), All Respiratory HA (age 65-99).
- Similarly, we sum across non-overlapping cardiovascular hospitalization effects, i.e., we sum the value for cardiovascular less AMI hospitalization for ages 18-64 and that for ages 65+.

Valuing Premature Mortality

To estimate the monetary value of risk change in premature death, we used the “value of statistical lives” saved (VSL) approach, which is a summary measure for the value of small changes in mortality risk for a large number of people. The VSL approach applies information from several published value-of-life studies to determine a reasonable monetary value of

preventing premature mortality. Based on 26 published studies,² the mean value of avoiding one statistical death is estimated to be roughly \$9.4 million (2010\$ at 2017 income level).

There are a number of uncertainties in this estimate. The health science literature on air pollution indicates that several human characteristics affect the degree to which mortality risk affects an individual. For example, some age groups appear to be more susceptible to air pollution than others (e.g., the elderly and children). Health status prior to exposure also affects susceptibility. An ideal benefits estimate of mortality risk reduction would reflect these human characteristics, in addition to an individual's WTP to improve one's own chances of survival plus WTP to improve other individuals' survival rates.

The ideal measure would also take into account the specific nature of the risk reduction commodity that is provided to individuals, as well as the context in which risk is reduced. To measure this value, it is important to assess how reductions in air pollution reduce the risk of dying from the time that reductions take effect onward and how individuals value these changes. Each individual's survival curve, or the probability of surviving beyond a given age, should shift as a result of an environmental quality improvement. For example, changing the current probability of survival for an individual also shifts future probabilities of that individual's survival. This probability shift will differ across individuals because survival curves depend on such characteristics as age, health state, and the current age to which the individual is likely to survive.

There are other potentially important factors that go beyond the scope of this discussion. For additional details, EPA (2005, p. 4-57) has an in-depth discussion of the uncertainties underlying mortality valuation.

Present Discounted Value of Avoiding Future Mortality

The delay, or lag, between changes in PM_{2.5} exposures and changes in mortality rates is not precisely known. The current scientific literature on adverse health effects, such as those associated with PM_{2.5} (e.g., smoking-related disease), and the difference in the effect size estimated in chronic exposure studies versus daily mortality studies, suggests that it is likely that not all cases of avoided premature mortality associated with a given incremental reduction in PM_{2.5} exposure would occur in the same year as the exposure reduction.

Current EPA benefits analyses (U.S. EPA, 2006, p. 5-21) assume a 20-year lag structure, with 30 percent of premature deaths occurring in the first year, 50 percent occurring evenly over years 2 to 5 after the reduction in PM_{2.5}, and 20 percent occurring evenly over years 6 to 20 after the reduction in PM_{2.5}. It should be noted that the selection of a 20-year lag structure is not directly supported by any PM_{2.5}-specific literature. Rather, it is intended to be a best guess at the appropriate time distribution of avoided cases of PM_{2.5}-related mortality. As noted by EPA, the

² These 26 studies have been identified in the Section 812 Reports to Congress as "applicable to policy analysis." This represents an intermediate value from a variety of estimates, and it is a value EPA has frequently used in Regulatory Impact Analyses (RIAs) as well as in the Section 812 Retrospective and Prospective Analyses of the Clean Air Act.

distribution of deaths over the latency period is intended to reflect the contribution of short-term exposures in the first year, cardiopulmonary deaths in the 2- to 5-year period, and long-term lung disease and lung cancer in the 6- to 20-year period. Finally, it is important to keep in mind that changes in the lag assumptions do not change the total number of estimated deaths but rather the timing of those deaths.

Specifying the lag is important because people are generally willing to pay more for something now than for the same thing later. They would, for example, be willing to pay more for a reduction in the risk of premature death in the same year as exposure is reduced than for that same risk reduction to be received the following year. This time preference for receiving benefits now rather than later is expressed by discounting benefits received later. There is an ongoing discussion within the federal government about the choice of a discount rate in this context: a 3% discount rate is recommended by EPA, while a 7% is recommended by OMB. Therefore, the users now have the ability to specify the discount rate—3% or 7%—for a COBRA session. Following EPA’s Guidelines for Preparing Economic Analyses (U.S. EPA, 2010a), COBRA users are recommended to calculate monetized health benefits using both discount rates and to evaluate whether (and to what extent) the overall outcome of their analysis is affected by the choice of discount rate.

Following EPA (2006, p. 5-21), COBRA assumes that some of the incidences of premature mortality related to PM_{2.5} exposures occur in a distributed fashion over the 20 years following exposure. To take this into account in the valuation of reductions in premature mortality, we applied an annual 3 percent discount rate to the value of premature mortality occurring in future years. Note that this lag adjustment does not apply to infant mortality, because Woodruff et al. (1997) estimate the number of infant deaths occurring in the same year as the emissions change.

Valuing Non-Fatal Myocardial Infarction

We are not able to identify a suitable WTP value for reductions in the risk of non-fatal heart attacks. Instead, we have used a cost-of-illness unit value with two components: the direct medical costs and the opportunity cost (lost earnings) associated with the illness event. Because the costs associated with a heart attack extend beyond the initial event itself, we considered costs incurred over several years. For opportunity costs, we used values derived from Cropper and Krupnick (Cropper & Sussman, 1990), originally used in the 812 Retrospective Analysis of the Clean Air Act (U.S. EPA, 1997). For the direct medical costs, we found three possible sources in the literature.

Wittels et al. (1990) estimated expected total medical costs of myocardial infarction over five years to be \$51,211 (in 1986\$) for people who were admitted to the hospital and survived hospitalization. (There does not appear to be any discounting used.) Using the CPI-U for medical care, the Wittels et al. estimate is \$163,050 in year 2010\$. This estimated cost is based on a medical cost model, which incorporated therapeutic options, projected outcomes and prices (using “knowledgeable cardiologists” as consultants).

The model used medical data and medical decision algorithms to estimate the probabilities of certain events and/or medical procedures being used. The authors noted that the average length of hospitalization for acute myocardial infarction has decreased over time (from an average of 12.9 days in 1980 to an average of 11 days in 1983). Wittels et al. used 10 days as the average in their study. It is unclear how much further the length of stay may have decreased from 1983 to the present. The average length of stay for ICD code 410 (myocardial infarction) in 2009 is 4.9 days (Agency for Healthcare Research and Quality, 2010). However, this may include patients who died in the hospital (not included among our non-fatal cases), whose length of stay was therefore substantially shorter than it would be if they hadn't died.

Eisenstein et al. (2001) estimated 10-year costs of \$44,663, in 1997\$, or \$73,950 in 2010\$ for myocardial infarction patients, using statistical prediction (regression) models to estimate inpatient costs. Only inpatient costs (physician fees and hospital costs) were included.

Russell et al. (1998) estimated first-year direct medical costs of treating nonfatal myocardial infarction of \$15,540 (in 1995\$), and \$1,051 annually thereafter. Converting to year 2010\$, that would be \$33,260 (3% discount rate) and \$31,446 (7% discount rate) for a 5-year period.

As seen in Exhibit F-4, the three different studies provided significantly different values. We have not adequately resolved the sources of differences in the estimates. Because the wage-related opportunity cost estimates from Cropper and Krupnick (1990) cover a 5-year period, we used a simple average of the two estimates for medical costs that similarly cover a 5-year period (i.e., assign a subjective weight of 0.5 to each estimate). We added this to the 5-year opportunity cost estimate. Exhibit F-5 gives the resulting estimates.

Exhibit F-4. Summary of Studies Valuing Reduced Incidences of Myocardial Infarction

Study	Direct Medical Costs (2010 \$, 3% DR)	Direct Medical Costs (2010 \$, 7% DR)	Over an x-year period, for x =
Wittels et al., 1990 ^a	\$163,050	\$163,050	5
Russell et al., 1998	\$33,260	\$31,446	5
Eisenstein et al., 2001	\$73,950	\$73,950	10

^a Wittels et al. did not appear to discount costs incurred in future years.

Exhibit F-5. Estimated Costs Over a 5-Year Period of a Non-Fatal Myocardial Infarction

Age Group	Opportunity Cost (2010 \$, 3% DR) ^a	Opportunity Cost (2010 \$, 7% DR) ^a	Medical Cost (2010 \$, 3% DR) ^b	Medical Cost (2010 \$, 7% DR) ^b	Total Cost (2010 \$, 3% DR)	Total Cost (2010 \$, 7% DR)
0 - 24	\$0	\$0	\$98,155	\$97,248	\$98,155	\$97,248
25-44	\$11,825	\$10,587	\$98,155	\$97,248	\$109,980	\$107,835
45 - 54	\$17,429	\$15,605	\$98,155	\$97,248	\$115,584	\$112,853
55 - 65	\$100,744	\$90,196	\$98,155	\$97,248	\$198,899	\$187,444
> 65	\$0	\$0	\$98,155	\$97,248	\$98,155	\$97,248

^a From Cropper and Krupnick (1990). Present discounted value of 5 years of lost earnings, adjusted from 1977\$ to 2010\$ using CPI-U “all items”.

^b An average of the 5-year costs estimated by Wittels et al. (1990) and Russell et al. (1998). Note that Wittels et al. appears not to have used discounting in deriving a 5-year cost; Russell et al. estimated first-year direct medical costs and annual costs thereafter. Medical costs were inflated to 2010\$ using CPI-U for medical care.

Valuing Hospital Admissions

Society’s WTP to avoid a hospital admission includes medical expenses, lost work productivity, the non-market costs of treating illness (i.e., air, water and solid waste pollution from hospitals and the pharmaceutical industry), as well as WTP of the affected individual, as well as of that of relatives, friends, and associated caregivers, to avoid the pain and suffering.³

Because medical expenditures are to a significant extent shared by society, via medical insurance, Medicare, etc., the medical expenditures actually incurred by the individual are likely to be less than the total medical cost to society. The total value to society of an individual’s avoidance of hospital admission, then, might be thought of as having two components: (1) the cost of illness (COI) to society, including the total medical costs plus the value of the lost productivity, as well as (2) the WTP of the individual, as well as that of others, to avoid the pain and suffering resulting from the illness.

In the absence of estimates of social WTP to avoid hospital admissions for specific illnesses (components 1 plus 2 above), estimates of total COI (component 1) are typically used as conservative (lower bound) estimates. Because these estimates do not include the value of avoiding the pain and suffering resulting from the illness (component 2), they are biased

³ Some people take action to avert the negative impacts of pollution. While the costs of successful averting behavior should be added to the sum of the health-endpoint-specific costs when estimating the total costs of pollution, these costs are not associated with any single health endpoint. It is possible that in some cases the averting action was not successful, in which case it might be argued that the cost of the averting behavior should be added to the other costs listed (for example, it might be the case that an individual incurs the costs of averting behavior and in addition incurs the costs of the illness that the averting behavior was intended to avoid). Because averting behavior is generally not taken to avoid a particular health problem (such as a hospital admission for respiratory illness), but instead is taken to avoid the entire collection of adverse effects of pollution, it does not seem reasonable to ascribe the entire costs of averting behavior to any single health endpoint. However, omission of these averting behavior costs will tend to bias the estimates downward.

downward. Some analyses adjust COI estimates upward by multiplying by an estimate of the ratio of WTP to COI, to better approximate total WTP. Other analyses have avoided making this adjustment because of the possibility of over-adjusting – that is, possibly replacing a known downward bias with an upward bias. The COI values used in this benefits analysis will not be adjusted to better reflect the total WTP.

Following the method used in the §812 analysis (U.S. EPA, 1999), ICD-code-specific COI estimates used in our analysis consist of two components: estimated hospital charges and the estimated opportunity cost of time spent in the hospital (based on the average length of a hospital stay for the illness). The opportunity cost of a day spent in the hospital is estimated as the value of the lost daily wage, regardless of whether or not the individual is in the workforce. The median daily wage was calculated by dividing the median weekly wage (\$695 in 2007 dollar or \$564.3 in 2000 dollar) by 5. The median weekly wages for 2007 was obtained from the U.S. Census Bureau, Statistical Abstract of the United States: 2009, Section 12, Table 626: “Full-Time Wage and Salary Workers – Numbers and Earnings: 2000 to 2007”.

For all hospital admissions endpoints available in this analysis, estimates of hospital charges and lengths of hospital stays were based on discharge statistics provided by the Agency for Healthcare Research and Quality’s Healthcare Utilization Project National Inpatient Sample (NIS) database (2007). The NIS is the largest inpatient care database in the United States, and it is the only national hospital database containing charge information on all patients. It contains data from a very large nationally representative sample of about eight million hospital discharges, and therefore provides the best estimates of mean hospital charges and mean lengths of stay available, with negligible standard errors. The sampling frame for the 2007 NIS is a sample of hospitals that comprises approximately 90 percent of all hospital discharges in the United States. Since the NIS is based on discharge samples, the discharge-level weight was used to weight discharges in order to produce national estimates. The principle diagnoses (based on ICD-9 codes) were used to define the health endpoints.

Since most pollution-related hospital admissions are likely unscheduled, the unit values of avoided hospital admissions used in COBRA are based solely on unscheduled hospitalizations. The total COI for an ICD-code-specific hospital stay lasting n days is estimated as the mean hospital charge plus n times the daily lost wage. The hospital admissions for which unit values are available in COBRA are given in Exhibit F-1.

Because of distortions in the market for medical services, the hospital charge may exceed “the cost of a hospital stay.” We use the example of a hospital visit to illustrate the problem. Suppose a patient is admitted to the hospital to be treated for an asthma episode. The patient’s stay in the hospital (including the treatments received) costs the hospital a certain amount. This is the hospital cost – i.e., the short-term expenditures of the hospital to provide the medical services that were provided to the patient during his hospital stay. The hospital then charges the payer a certain amount – the hospital charge. If the hospital wants to make a profit, is trying to cover costs that are not associated with any one particular patient admission (e.g., uninsured patient services), and/or has capital expenses (building expansion or renovation) or other long term

costs, it may charge an amount that exceeds the patient-specific short term costs of providing services. The payer (e.g., the health maintenance organization or other health insurer) pays the hospital a certain amount – the payment – for the services provided to the patient. The less incentive the payer has to keep costs down, the closer the payment will be to the charge. If, however, the payer has an incentive to keep costs down, the payment may be substantially less than the charge; it may still, however, exceed the short-term cost for services to the individual patient.

Although the hospital charge may exceed the short-term cost to the hospital of providing the medical services required during a patient’s hospital stay, cost of illness estimates based on hospital charges are still likely to understate the total social WTP to avoid the hospitalization in the first place, because the omitted WTP to avoid the pain and suffering is likely to be quite large.

Valuing Emergency Room Visits for Asthma

To value asthma emergency room (ER) visits, we used a simple average of two estimates from the literature. The first estimate comes from Smith et al.(1997), who reported that there were approximately 1.2 million asthma-related ER visits made in 1987, at a total cost of \$186.5 million, in 1987\$. The average cost per visit was therefore \$155 in 1987\$, or \$464 in 2010 \$ (using the CPI-U for medical care to adjust to 2010 \$). The second is from Stanford et al. (1999), who examined data from asthmatics from 1996-1997, and reported an average cost of \$388 (2010 \$). We use a simple average of the two estimates, which yields a unit value of about \$426 (2010 \$).

In comparing their study to Smith et al. (1997), Stanford et al. (1999) noted that the data used by Smith et al., “may not reflect changes in treatment patterns during the 1990s.” In addition, its costs are the costs to the hospital (or ER) for treating asthma rather than charges or payments by the patient and/or third party payer. Costs to the ER are probably a better measure of the value of the medical resources used up on an asthma ER visit.

Valuing Acute Symptoms and Illness Not Requiring Hospitalization

Several acute symptoms and illnesses have been associated with air pollution, including acute bronchitis in children, upper and lower respiratory symptoms, and exacerbation of asthma (as indicated by one of several symptoms whose occurrence in an asthmatic generally suggests the onset of an asthma episode). In addition, several more general health endpoints which are associated with one or more of these acute symptoms and illnesses, such as minor restricted activity days and work loss days, have also been associated with air pollution.

Valuing Acute Bronchitis in Children

Estimating WTP to avoid a case of acute bronchitis is difficult for several reasons. First, WTP to avoid acute bronchitis itself has not been estimated. Estimation of WTP to avoid this health endpoint therefore must be based on estimates of WTP to avoid symptoms that occur with this illness. Second, a case of acute bronchitis may last more than one day, whereas it is a day of avoided symptoms that is typically valued. Finally, the C-R function used in the benefit analysis for acute bronchitis was estimated for children, whereas WTP estimates for those symptoms associated with acute bronchitis were obtained from adults.

In previous benefits analyses, such as in the §812 Prospective analysis (U.S. EPA, 1999), acute bronchitis was valued at \$59.31 (in 2000 \$ and at 1990 income level). This is the midpoint between a low estimate and a high estimate. The low estimate is the sum of the midrange values recommended by IEc (1994) for two symptoms believed to be associated with acute bronchitis: coughing and chest tightness. The high estimate was taken to be twice the value of a minor respiratory restricted activity day. For a more complete description of the derivation of this estimate, see Abt Associates (2000, p. 4-30).

A unit value of \$59.31 assumes that an episode of acute bronchitis lasts only one day. However, this is generally not the case. More typically, it can last for 6 or 7 days. We therefore made a simple adjustment, multiplying the original unit value of \$59.31 by 6. The unit value thus derived and used was \$356 in 2000 \$ and at 1990 income level ($=\$59.31 \times 6$) or \$477 in 2010 \$ and at 2017 income level.

Valuing Upper Respiratory Symptoms (URS) in Children

Willingness to pay to avoid a day of upper respiratory symptoms is based on symptom-specific WTPs to avoid those symptoms identified by Pope et al. (1991) as part of the complex of upper respiratory symptoms. Three contingent valuation studies have estimated WTP to avoid various morbidity symptoms that are either within the complex defined by Pope et al. (1991), or are similar to those symptoms. In each CV study, participants were asked their WTP to avoid a day of each of several symptoms. The WTP estimates corresponding to the morbidity symptoms valued in each study are presented in Exhibit F-7.

The three individual symptoms listed in Exhibit F-7 that were identified as most closely matching those listed by Pope, et al. (1991) for upper respiratory symptoms are cough, head/sinus congestion, and eye irritation, corresponding to “wet cough,” “runny or stuffy nose,” and “burning, aching or red eyes,” respectively. A day of upper respiratory symptoms could consist of any one of the seven possible “symptom complexes” consisting of at least one of these three symptoms. These seven possible symptom complexes are presented in Exhibit F-8. We assumed that each of these seven complexes is equally likely.⁴ The point estimate of WTP is just an average of the seven estimates of WTP for the different complexes.

⁴ With empirical evidence, we could presumably improve the accuracy of the probabilities of occurrence of each type of URS. Lacking empirical evidence, however, a uniform distribution seems the most reasonable “default” assumption.

A unit value of \$32.99 (at 2017 income level and in 2010 \$) assumes that an episode of the symptoms lasts only one day.

Exhibit F-7. Median WTP Estimates and Derived Midrange Estimates (2017 income level, 2010 \$)^a

Symptom ^b	Dickie et al. (1987)	Tolley et al. (1986)	Loehman et al. (1979)	Mid-Range Estimate
Throat congestion	6.66	28.85	-	17.65
Head/sinus congestion	7.77	31.07	14.46	17.65
Coughing	2.22	24.43	8.79	12.36
Eye irritation	-	27.72	-	27.72
Headache	2.22	44.40	-	17.65
Shortness of breath	0.00	-	18.64	8.81
Pain upon deep inhalation (PDI)	7.79	-	-	7.79
Wheeze	4.45	-	-	4.45
Coughing up phlegm	4.86 ^c	-	-	4.86
Chest tightness	11.12	-	-	11.12

^a Values were inflated to 2010 \$ using CPI-U for “all items” and adjusted to 2017 income level.

^b All estimates are WTP to avoid one day of symptom. Midrange estimates were derived by IEC (1993).

^c 10% trimmed mean.

Exhibit F-8. Estimates of WTP to Avoid Upper Respiratory Symptoms (2017 income level, 2010 \$)^a

Symptom Combinations Identified as URS by Pope et al. (1991)	WTP to Avoid Symptom(s)
Coughing	\$12.36
Head/Sinus Congestion	\$17.65
Eye Irritation	\$27.72
Coughing, Head/Sinus Congestion	\$30.01
Coughing, Eye Irritation	\$40.08
Head/Sinus Congestion, Eye Irritation	\$45.37
Coughing, Head/Sinus Congestion, Eye Irritation	\$57.73
Average: \$32.99	

^a Values were inflated to 2010 \$ and adjusted to 2017 income level.

Valuing Lower Respiratory Symptoms (LRS) in Children

Schwartz et al. (1994, p. 1235) defined lower respiratory symptoms as at least two of the following symptoms: cough, chest pain, phlegm, and wheeze. To value this combination of symptoms, we used the same method as we did for upper respiratory symptoms. We chose those

individual health effects that seem most consistent with lower respiratory symptoms, we derived all of the possible combinations of these symptoms, and then we valued these combinations.

The symptoms for which WTP estimates are available that reasonably match lower respiratory symptoms are: cough (C), chest tightness (CT), coughing up phlegm (CP), and wheeze (W). A day of lower respiratory symptoms could consist of any one of the 11 combinations of at least two of these four symptoms.⁵ We assumed that each of the eleven types of lower respiratory symptoms is equally likely,⁶ and the mean WTP is the average of the WTPs over all combinations. Exhibit F-9 presents resulting estimate.

Exhibit F-9. Estimates of WTP to Avoid Lower Respiratory Symptoms (2017 income level and 2010 \$)

Symptom Combinations Identified as LRS by Schwartz et al. (1994, p. 1235)	WTP to Avoid Symptoms
Coughing, Chest Tightness	\$23.46
Coughing, Coughing Up Phlegm	\$17.20
Coughing, Wheeze	\$16.79
Chest Tightness, Coughing Up Phlegm	\$15.96
Chest Tightness, Wheeze	\$15.56
Coughing Up Phlegm, Wheeze	\$9.31
Coughing, Chest Tightness, Coughing Up Phlegm	\$28.33
Coughing, Chest Tightness, Wheeze	\$27.92
Coughing, Coughing Up Phlegm, Wheeze	\$21.66
Chest Tightness, Coughing Up Phlegm, Wheeze	\$20.42
Coughing, Chest Tightness, Coughing Up Phlegm, Wheeze	\$32.77
	Average: \$20.85

Valuing Work Loss Days (WLDs)

Willingness to pay to avoid the loss of one day of work was estimated by dividing median annual earnings (\$41,525.5 in 2010\$) by (52 × 5), which resulted a unit value of \$160 (2010\$). The median annual earnings for males and females were obtained from U.S. Census Bureau, 2010 American Community Survey, Table B20017: “Median earnings in the past 12 months (in 2010

⁵ Because cough is a symptom in some of the upper respiratory symptom clusters as well as some of the lower respiratory symptom clusters, there is the possibility of a very small amount of double counting – if the same individual were to have an occurrence of upper respiratory symptoms which included cough and an occurrence of lower respiratory symptoms which included cough *both on exactly the same day*. Because this is probably a very small probability occurrence, the degree of double counting is likely to be very minor. Moreover, because upper respiratory symptoms is applied only to asthmatics ages 9-11 (a very small population), the amount of potential double counting should be truly negligible.

⁶ As with URS, if we had empirical evidence we could improve the accuracy of the probabilities of occurrence of each type of LRS. Lacking empirical evidence, however, a uniform distribution seems the most reasonable “default” assumption.

inflation-adjusted dollars) by sex by work experience in the past 12 months for the population 16 years and over with earnings in the past 12 months.” Overall earnings were calculated as the simple average of full-time male earnings and full-time female earnings. Valuing the loss of a day’s work at the wages lost is consistent with economic theory, which assumes that an individual is paid exactly the value of his labor.

The use of the median rather than the mean, however, requires some comment. If all individuals in society were equally likely to be affected by air pollution to the extent that they lose a day of work because of it, then the appropriate measure of the value of a work loss day would be the mean daily wage. It is highly likely, however, that the loss of work days due to pollution exposure does not occur with equal probability among all individuals, but instead is more likely to occur among lower income individuals than among high income individuals. It is probable, for example, that individuals who are vulnerable enough to the negative effects of air pollution to lose a day of work as a result of exposure tend to be those with generally poorer health care. Individuals with poorer health care have, on average, lower incomes.

To estimate the average lost wages of individuals who lose a day of work because of exposure to PM_{2.5} pollution, then, would require a weighted average of all daily wages, with higher weights on the low end of the wage scale and lower weights on the high end of the wage scale. Because the appropriate weights are not known, however, the median wage was used rather than the mean wage. The median is more likely to approximate the correct value than the mean because means are highly susceptible to the influence of large values in the tail of a distribution (in this case, the small percentage of very large incomes in the United States), whereas the median is not susceptible to these large values.

Valuing Minor Restricted Activity Days (MRADs)

No studies are reported to have estimated WTP to avoid a minor restricted activity day (MRAD). However, IEc (1993) has derived an estimate of WTP to avoid a minor respiratory restricted activity day (MRRAD), using WTP estimates from Tolley et al. (1986) for avoiding a three-symptom combination of coughing, throat congestion, and sinusitis. This estimate of WTP to avoid a MRRAD, so defined, is \$38.37 (1990 \$), or after adjusting for inflation and income growth \$68 (2017 income level and 2010 \$). Although Ostro and Rothschild (1989) estimated the relationship between PM_{2.5} and MRADs, rather than MRRADs (a component of MRADs), it is likely that most of the MRADs associated with exposure to PM_{2.5} are in fact MRRADs. For the purpose of valuing this health endpoint, then, we assumed that MRADs associated with PM_{2.5} exposure may be more specifically defined as MRRADs, and therefore used the estimate of mean WTP to avoid a MRRAD.

Any estimate of mean WTP to avoid a MRRAD (or any other type of restricted activity day other than WLD) will be somewhat arbitrary because the endpoint itself is not precisely defined. Many different combinations of symptoms could presumably result in some minor or less minor restriction in activity. Krupnick and Kopp (1988) argued that mild symptoms will not be sufficient to result in a MRRAD, so that WTP to avoid a MRRAD should exceed WTP to avoid any single mild symptom. A single severe symptom or a combination of symptoms could,

however, be sufficient to restrict activity. Therefore WTP to avoid a MRRAD should, these authors argue, not necessarily exceed WTP to avoid a single severe symptom or a combination of symptoms. The “severity” of a symptom, however, is similarly not precisely defined; moreover, one level of severity of a symptom could induce restriction of activity for one individual while not doing so for another. The same is true for any particular combination of symptoms.

Valuing Asthma Exacerbations

Rowe and Chestnut (1986) surveyed asthmatics to estimate WTP for avoidance of a “bad asthma day,” as defined by the subjects. For purposes of valuation, an asthma attack is assumed to be equivalent to a day in which asthma is moderate or worse as reported in the Rowe and Chestnut study. Using the mean of average WTP estimates for the four severity definitions of a “bad asthma day,” the asthma exacerbation could be valued at \$57.5 (2017 income level and 2010 \$) per incidence.

Appendix G: Additional Quick Start Tutorials on Sample COBRA Scenarios

You can use COBRA to estimate the impacts of a new policy or program that results in a change in air pollution. This appendix provides two case studies to give you a quick introduction on how to work through the steps of a simple analysis for a few types of policies: renewable energy supply goals or standards and energy efficiency programs.

Estimating the Benefits of Clean Energy Policies

Quickstart Tutorial: How To Use The Co-Benefits Risk Assessment (COBRA) Screening Model

Analytical Steps and Case Studies



June, 2015

Overview of Presentation



- How to conduct an analysis with COBRA
 - Summarizes four key analytical steps
- Two case studies illustrate how to apply these steps in two clean energy scenarios:
 1. Renewable Portfolio Standard
 2. Energy Efficiency Programs in Public Buildings

2

How to Conduct an Analysis with COBRA

Analytical Steps and Relevant Resources





Steps in COBRA Analysis



1. Estimate where (e.g., in one or more counties or states, regionally, nationally) and what emission reductions will take place



2. Enter the location, types, and quantity of emission reductions expected from the policy or activity in COBRA



3. Select a discount rate in COBRA to appropriately discount the value of future benefits

4. Run the model and review the results

This presentation will:

- Walk you through these steps, and
- Lead you to other tools and resources that can help you develop your inputs.

COBRA uses your inputs to estimate the air quality, health, and related economic impacts of the scenario

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Step 1: Estimate where and what emissions reductions will take place



• Decide on the geographic area where emissions are expected to change

• COBRA can assess actions that affect emissions in:

- a single county or state,
- groups of counties and states (contiguous or otherwise), or
- the entire nation

• COBRA allows you to vary the types and amounts of emissions changes expected to occur in different locations



• Estimating what and where electricity will be displaced and emissions reduced presents challenges due to the:

- Complex way electricity is generated and transmitted across the U.S.
- Uncertainty about future emissions in places with market-based environmental programs, such as cap and trade

• Simplifying assumptions can be made when using COBRA but a highly sophisticated energy analysis of the impacts of a clean energy policy on a location will generate more reliable results

• For more information about the complexity of the energy system, see Chapters 3 and 4 of *Assessing the Multiple Benefits of Clean Energy: A Resource for States*, available at

<http://www.epa.gov/state/localclimate/resources/benefits.html>

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Step 1: Estimate where and what emissions reductions will take place



- In COBRA, you can enter the emission changes as a percentage or in absolute terms
 - A **percentage** can be used when a policy is expected to reduce emissions or use of an energy source by a specific proportion
 - For example, for an increase in the use of renewable electricity generation by 20%, you could assume that the use of existing fuels for electricity generation would be reduced by 20%
 - An **absolute** number can be used for policies that do not lend themselves easily to percentage reductions or when you want to enter more specific emission changes
 - For example, 5,000 tons of sulfur dioxide

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Resources for Calculating Emissions Reductions from Electricity-related Policies



- If you do not have absolute emission reduction estimates, you can use:
 - A basic approach or tool, such as:
 - Applying an emission factor obtained from EPA's Emissions & Generation Resource Integrated Database (eGrid)
<http://www.epa.gov/cleanenergy/energy-resources/egrid/index.html>, OR
 - EPA's AVoided Emissions and geneRation Tool (AVERT)
<http://epa.gov/avert/>
 - More sophisticated approaches, such as those described in EPA guides:
 - *Assessing the Multiple Benefits of Clean Energy: A Resource for States*, Chapter 4
http://www.epa.gov/statelocalclimate/documents/pdf/epa_assessing_benefits_ch4.pdf
 - *Roadmap for Incorporating Energy Efficiency/Renewable Energy Policies and Programs into State and Tribal Implementation Plans*, Appendix I <http://www.epa.gov/airquality/eere/manual.html>

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Step 2: Select and enter the types, location and quantity of emission reductions expected



- You will need to know what source categories of emissions will be affected by the policy
- The emissions inventory in COBRA includes the 14 major emissions source categories (i.e., “tiers”) of criteria pollutants included in the National Emissions Inventory (NEI):*

- Chemical and Allied Product Manufacturing
- Fuel Combustion - Electric Utility
- Fuel Combustion - Industry
- Fuel Combustion - Other
- Highway Vehicles
- Metal Processing
- Miscellaneous
- Natural Sources (Biogenics)
- Off-Highway
- Other Industrial Processes
- Petroleum & Related Industries
- Solvent Utilization
- Storage & Transport
- Waste Disposal & Recycling

*For more on the 2008 NEI, see:
<http://www.epa.gov/ttnchie1/net/2008inventory.html>

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Step 2: Select and enter the types, location and quantity of emission reductions expected



- Often, clean energy investments, such as those that increase the use of renewable energy or energy efficiency, will affect the “fuel combustion from electric utilities” category
- Within each category, there are fuel choices, such as coal, gas, and oil
 - If you know the specific fuel will be affected, you may choose it
 - If not, you can use the broader category
- Enter the estimated emission reductions by the appropriate types and locations, ensuring that you save your inputs once you are finished

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Step 3: Select a discount rate



- A discount rate is used to appropriately discount the value of future benefits
- Not all benefits occur in the year of analysis, and people are generally willing to pay more for something now than for the same thing later
- COBRA accounts for this time preference by discounting benefits received later

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Step 3: Select a discount rate



- EPA's Guidelines for Economic Analysis recommend using both 3% and 7% discount rates to see how the conclusions of your analysis change. Both rates are available in COBRA
- The discount rate will affect the value of the benefits
 - A higher discount rate favors investments with immediate benefits and reduces the value of future benefits
 - A lower discount rate places a greater value on future benefits to society
- You can run your scenario with both rates and then evaluate the effect of the change in discount rate on the results

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Step 4: Run the model and review the results



- Once you have completed these four steps, you are ready to run the model, which will take a few minutes depending on the speed of your computer
- You can view the results for the changes in air quality, health effects, and related economic value in table and map forms
- You can export results as tables and copy/paste screenshots into reports and presentations

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Key Considerations when Interpreting Results



- COBRA is intended as a screening tool
 - COBRA does not predict the future but can be used to obtain ballpark health benefits estimates and to compare or rank options
 - When more detailed analyses are required, consider using more sophisticated modeling approaches

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Key Considerations when Interpreting Results



- There is uncertainty surrounding the values of key assumptions embedded in COBRA (i.e., emissions inventory, health impact functions, and economic values)
 - You should review the limitations and assumptions described in the COBRA User Manual

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Key Considerations when Interpreting Results



- Emissions in some states and regions are “capped” and firms may trade emission allowances
 - If you assume an emission reduction among power plants in a state, emissions from other power plants may increase unless emission allowances are retired as part of the assumed emission reduction
 - COBRA does not automatically capture this potential effect; it would need to be calculated in another model

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Case Study 1: Renewable Portfolio Standard



This case study illustrates how to conduct an analysis of a clean energy policy with COBRA using a renewable portfolio standard as an example.



Analyzing the Health Benefits of a Renewable Portfolio Standard with COBRA



- A renewable portfolio standard (RPS) requires electric utilities to switch a particular percentage of electricity generation to renewable sources
- If electricity had previously been generated with fossil fuels, the RPS will result in criteria air pollutant reductions and health benefits





Analyzing the Health Benefits of a Renewable Portfolio Standard with COBRA



- The next slides describe how to estimate the health and related economic benefits of a state or local RPS
 - Specifically, we assume a state (Michigan) has established an RPS requirement that 10% of electricity generation must be from renewable sources by 2015
 - We also could have looked at a county with a renewable target or requirement

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Step 1: Estimate where and what emissions reductions will take place



- Select what geographic locations you expect to be affected by the emissions change
 - You can enter emissions changes at the national, regional, state or county levels
 - If you know that specific plants will be affected, you can enter emissions changes only in those counties
 - Or you could use more sophisticated energy modeling approaches or tools to identify any and all plants that may be affected by a state or local RPS and manually enter those changes for the counties with affected plants

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Step 1: Estimate where and what emissions reductions will take place



- For the Michigan RPS, we assume that all emission changes will occur statewide
- In COBRA, we create a scenario for an individual state and select Michigan



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Step 1: Estimate where and what emissions reductions will take place



- To determine the emissions reduced, you can:
 - Assume that a switch of 10% of electricity generation from fossil fuels to renewable sources that do not generate air pollution will reduce 10% of all pollutants, or
 - Estimate absolute emission reductions using:
 - An emission factor approach as described earlier
 - A more sophisticated modeling approach, if available



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Step 1: Estimate where and what emissions reductions will take place



- For this example, we use emissions factors from EPA's Emissions & Generation Resource Integrated Database (eGrid)* to develop an absolute estimate
 - Using "eGRID2012 year 2009 Summary Tables (PDF)," we found:
 - Net electric generation in Michigan: **88 million MWh**
 - Non-baseload output emissions rates for Michigan:
 - SO₂: **6.6348 lbs. per MWh**
 - NO_x: **1.9392 lbs. per MWh**
 - Percentage of electric generation that already comes from renewable sources in Michigan: **3.1%**

* eGRID is available at <http://www.epa.gov/cleanenergy/energy-resources/egrid/index.html>

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Step 1: Estimate where and what emissions reductions will take place



- Since 3.1% of electric generation already comes from renewable sources, we assume our scenario will reduce emissions by:
 - $10\% - 3.1\% = 6.9\%$
- We calculate the reduction in MWh:
 - $6.9\% \times 88 \text{ million MWh} = 6 \text{ million MWh}$
- Assuming the renewable energy used does not emit any air pollution, we calculate the emission reductions as:
 - SO₂: $6 \text{ million MWh} \times 6.6348 \text{ per MWh} = 40 \text{ million lbs.}$
 - = **20,000 tons**
 - NO_x: $6 \text{ million MWh} \times 1.9392 \text{ per MWh} = 12 \text{ million lbs.}$
 - = **6,000 tons**

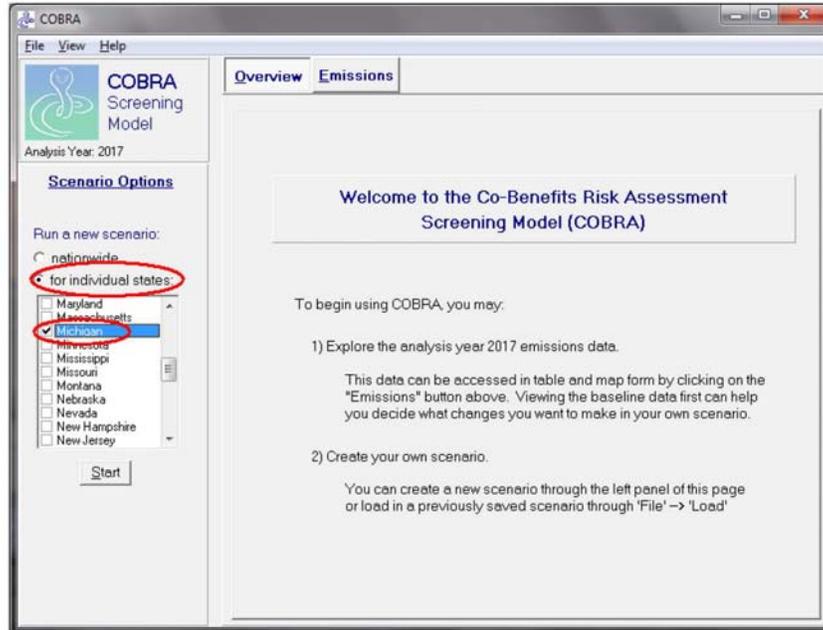
[Note that 1 ton = 2,000 lbs.]

23



Step 2: Set up Scenario in COBRA

(a) Location of Emission Reductions Expected



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Step 2: Set up Scenario in COBRA

(b) Types of Emission Reductions Expected



- A RPS affects the fuel combustion from electricity generation category
 - These categories include fuel choices (e.g., gas, coal)
 - You can select specific fuel choices that are expected to be affected if known or assume all fuel choices are affected
- For the Michigan RPS example, we assume that all fuel sources would be affected by the RPS (i.e., not just natural gas or just coal) and select the “fuel combustion from electricity generation” category

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Step 2: Set up Scenario in COBRA (b) Types of Emission Reductions Expected



Define scenario

MI

All Counties |

To change emissions estimates, click on a source category and enter your changes in the panel below. You MUST click the Apply Edits button after editing each source category for your changes to be recorded.

Currently active category:
FUEL COMB. ELEC. UTIL

- CHEMICAL & ALLIED PRODUCT MFG
- FUEL COMB. ELEC. UTIL
- FUEL COMB. INDUSTRIAL
- FUEL COMB. OTHER
- HIGHWAY VEHICLES
- METALS PROCESSING
- MISCELLANEOUS
- NATURAL SOURCES
- OFF-HIGHWAY
- OTHER INDUSTRIAL PROCESSES
- PETROLEUM & RELATED INDUSTRIES
- SOLVENT UTILIZATION
- STORAGE & TRANSPORT
- WASTE DISPOSAL & RECYCLING

PM 2.5: reduce by percent tons

SO₂: reduce by percent tons

NO_x: reduce by percent tons

NH₃: reduce by percent tons

VOC: reduce by percent tons

Apply Edits

<- Back Summarize Edits Run Scenario ->

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Step 2: Set up Scenario in COBRA (c) Quantity of emission reductions expected



Define scenario

MI

All Counties |

To change emissions estimates, click on a source category and enter your changes in the panel below. You MUST click the Apply Edits button after editing each source category for your changes to be recorded.

Currently active category:
FUEL COMB. ELEC. UTIL

- CHEMICAL & ALLIED PRODUCT MFG
- FUEL COMB. ELEC. UTIL
- FUEL COMB. INDUSTRIAL
- FUEL COMB. OTHER
- HIGHWAY VEHICLES
- METALS PROCESSING
- MISCELLANEOUS
- NATURAL SOURCES
- OFF-HIGHWAY
- OTHER INDUSTRIAL PROCESSES
- PETROLEUM & RELATED INDUSTRIES
- SOLVENT UTILIZATION
- STORAGE & TRANSPORT
- WASTE DISPOSAL & RECYCLING

PM 2.5: reduce by percent tons

SO₂: reduce by percent tons

NO_x: reduce by percent tons

NH₃: reduce by percent tons

VOC: reduce by percent tons

Apply Edits

<- Back Summarize Edits Run Scenario ->

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Step 3: Select a discount rate



- A discount rate is used to appropriately discount the value of future benefits
- In this case study, we use a 3% discount rate
- This discount rate provides an upper bound for the estimated benefits and places a greater value on future benefits to society, compared to higher discount rates

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Step 3: Select a discount rate



Select a Discount Rate for the Scenario

 COBRA estimates the economic value of current and future avoided deaths and illnesses expected based on emissions reductions in the year 2017. Emission reductions require investments and, like all investments, there are trade-offs, or opportunity costs, of picking one investment over another, each with their own set and schedule of expected benefits. To reflect the opportunity costs of the investments foregone by investing in emission reductions and to figure out how much future benefits are worth today, COBRA users must select a discount rate.

Rather than using just a single rate, EPA's Guidelines for Economic Analysis recommend that analysts use a bounding approach to discounting, developing an upper and lower bound for their estimates. They advise use of both:

- a 3% rate, reflecting the interest rate consumers might earn on Government backed securities, and
- a 7% rate, reflecting the opportunity cost of private capital, based on estimates from the Office of Management and Budget.

NOTE: A higher discount rate favors those investments with immediate benefits and reduces the value of future benefits more than a lower discount rate, which places a greater value on future benefits to society. For more information on discount rates and how EPA uses them in monetizing health benefits, see the User Manual.

In order to run the COBRA model, please select a discount rate to use in this COBRA session.

3%
 7%

Continue

29



Step 4: Run the model and review the results



We calculated absolute emissions reductions of Michigan's renewable portfolio standard of 10%.

Annual Emission Reductions (short tons)	
Pollutant	Amount
Sulfur Dioxide (SO ₂)	20,000
Nitrogen Oxides (NO _x)	6,000

COBRA (1) converted emissions reductions into air quality improvements, and (2) estimated annual adverse health impacts avoided.

Annual Adverse Health Impacts Avoided	
Outcome	Number
Mortality	85 - 192
Asthma Exacerbations	2,271
Heart Attacks	11 - 99
Hospital Admissions	55
Acute Bronchitis	117
Respiratory Symptoms	3,636
Asthma ER Visits	46
Minor Restricted Activity Days	61,181
Work Days Lost	10,227

COBRA monetized the value or benefits of the avoided adverse health effects.

Annual Benefits (2010, \$1,000s)	
	Dollar Value
	\$715,980 - \$1,620,219
	\$130
	\$1,304 - \$12,114
	\$1,853
	\$56
	\$102
	\$20
	\$4,143
	\$1,633
total	\$725,221 - \$1,640,270

* Don't forget to consider the caveats from slides 13 through 15

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Case Study 2: Wind Energy Program



This case study illustrates how to conduct an analysis of a clean energy program with COBRA using wind energy capacity as an example.





Using COBRA to Evaluate the Benefits of Wind Energy Production



- Wind energy is used across the country, whether it is produced in-state or purchased from other states
- If the electricity had previously been generated with fossil fuels, wind energy production can lead to criteria air pollutant reductions and health benefits

For more details, see: the American Wind Energy Association's "The Clean Air Benefits of Wind Energy" report, available at http://awea.files.cms-plus.com/FileDownloads/pdfs/AWEA_Clean_Air_Benefits_WhitePaper%20Final.pdf.

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Using COBRA to Evaluate Wind Energy Production



- The next slides describe how to estimate the health and related economic benefits of increasing a state's wind energy capacity
 - Specifically, we assume Texas has decided to explore the benefits associated with a new wind energy program

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Step 1: Estimate where and what emissions reductions will take place



- Select what geographic locations you expect to be affected by the emissions change
 - You can enter emissions changes at the national, regional, state or county levels
 - If you know that specific plants will be affected, you can enter emissions changes only in those counties
 - Or you could use more sophisticated energy modeling approaches or tools to identify any and all plants that may be affected by a state or local wind energy program and enter those changes in manually

34



Step 1: Estimate where and what emissions reductions will take place



- For this example, we assume that the wind energy impacts will take place throughout Texas
- Due to the interconnectedness of the grid, these impacts will affect electricity providers and emissions beyond this state

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Step 1: Estimate where and what emissions reductions will take place



- To estimate the electricity reductions expected from the program, you can either:
 - Estimate how many MW you expect to save, or
 - Find a similar program to use as a proxy
- In this hypothetical example, we estimate emissions reductions due to a 7,000 MW wind energy program in Texas
 - The American Wind Energy Association (AWEA) reported installed wind power capacity by state, with a total of 12,355 MW for Texas*
 - Another 7,000 MW of wind energy projects are currently under construction in Texas*

*Source: AWEA's "AWEA U.S. Wind Industry Fourth Quarter 2013 Market Report", available at <http://www.awea.org/4q2013>.

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Step 1: Estimate where and what emissions reductions will take place



- To estimate the annual emissions reduced from 7,000 MW of installed wind capacity, you can use:
 - A basic tool that estimates emissions reductions from renewable energy programs
 - A more sophisticated modeling approach, if available

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Step 1: Estimate where and what emissions reductions will take place



- For this example, we use EPA’s AVOIDed Emissions and geneRation Tool (AVERT)* to:
 - Apply a 7,000 MW increase in installed wind capacity in Texas
 - Calculate the county-level emission reductions (in lbs)
 - Sum the emission reductions to state level
 - Convert emissions reductions to tons

For more details, EPA’s AVERT tool and documentation are available at <http://epa.gov/avert/>.

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Step 1: Estimate where and what emissions reductions will take place



- Annual emission reductions (in tons) from 7,000 MW wind energy program using AVERT:

State/County	SO ₂	NO _x
Texas	31,738.6	12,722.9
Oklahoma*	0.75	64.75

*Note that Oklahoma also experiences emissions reductions from the wind program.

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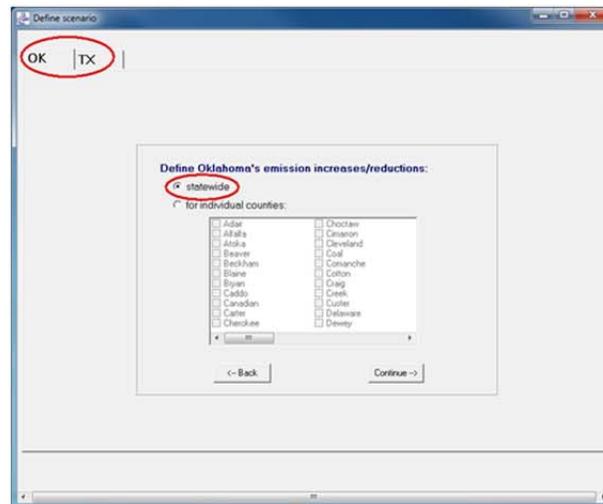


Step 2: Set up Scenario in COBRA

(a) Location of Emission Reductions Expected



- Emission reductions in all affected states are input at the state level



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Step 2: Set up Scenario in COBRA

(b) Types of Emission Reductions Expected



- Since renewable energy programs affect electricity generation, the affected emissions category is “fuel combustion from electricity generation”
- This category includes fuel choices (e.g., gas, coal)
- Since all fuel sources could be affected by the renewable energy program, select the “fuel combustion from electricity generation” category

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Step 2: Set up Scenario in COBRA (b) Types of Emission Reductions Expected



- Select emissions category for each affected state or county

Define scenario

OK TX

All Counties

To change emissions estimates, click on a source category and enter your changes in the panel below. You MUST click the Apply Edits button after editing each source category for your changes to be recorded.

Currently active category:
FUEL COMB ELEC UTIL

CHEMICAL & ALLIED PRODUCT MFG
 FUEL COMB ELEC UTIL
 FUEL COMB INDUSTRIAL
 FUEL COMB OTHER
 HIGHWAY VEHICLES
 METALS PROCESSING
 MISCELLANEOUS
 NATURAL SOURCES
 OFF-HIGHWAY
 OTHER INDUSTRIAL PROCESSES
 PETROLEUM & RELATED INDUSTRIES
 SOLVENT UTILIZATION
 STORAGE & TRANSPORT
 WASTE DISPOSAL & RECYCLING

PM 2.5: reduce by percent
 increase by tons

SO₂: reduce by percent
 increase by tons

NO_x: reduce by percent
 increase by tons

NH₃: reduce by percent
 increase by tons

VOC: reduce by percent
 increase by tons

Apply Edits

<- Back Summarize Edits Run Scenario ->

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Step 2: Set up Scenario in COBRA (c) Quantity of emission reductions expected



- Enter emission reductions for each affected state or county
 - Do not forget to enter and click “Apply Edits” for each state/county

Define scenario

OK TX

All Counties

To change emissions estimates, click on a source category and enter your changes in the panel below. You MUST click the Apply Edits button after editing each source category for your changes to be recorded.

Currently active category:
FUEL COMB ELEC UTIL

CHEMICAL & ALLIED PRODUCT MFG
 FUEL COMB ELEC UTIL
 FUEL COMB INDUSTRIAL
 FUEL COMB OTHER
 HIGHWAY VEHICLES
 METALS PROCESSING
 MISCELLANEOUS
 NATURAL SOURCES
 OFF-HIGHWAY
 OTHER INDUSTRIAL PROCESSES
 PETROLEUM & RELATED INDUSTRIES
 SOLVENT UTILIZATION
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 WASTE DISPOSAL & RECYCLING

PM 2.5: reduce by percent
 increase by tons

SO₂: reduce by percent
 increase by tons

NO_x: reduce by percent
 increase by tons

NH₃: reduce by percent
 increase by tons

VOC: reduce by percent
 increase by tons

Apply Edits

<- Back Summarize Edits Run Scenario ->

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Step 3: Select a discount rate



- A discount rate is used to appropriately discount the value of future benefits
- In this case study, we use a 3% discount rate
- This discount rate provides an upper bound for the estimated benefits and places a greater value on future benefits to society, compared to higher discount rates

44



Step 3: Select a discount rate



Select a Discount Rate for the Scenario

 COBRA estimates the economic value of current and future avoided deaths and illnesses expected based on emissions reductions in the year 2017. Emission reductions require investments and, like all investments, there are trade-offs, or opportunity costs, of picking one investment over another, each with their own set and schedule of expected benefits. To reflect the opportunity costs of the investments foregone by investing in emission reductions and to figure out how much future benefits are worth today, COBRA users must select a discount rate.

Rather than using just a single rate, EPA's Guidelines for Economic Analysis recommend that analysts use a bounding approach to discounting, developing an upper and lower bound for their estimates. They advise use of both:

- a 3% rate, reflecting the interest rate consumers might earn on Government backed securities, and
- a 7% rate, reflecting the opportunity cost of private capital, based on estimates from the Office of Management and Budget.

NOTE: A higher discount rate favors those investments with immediate benefits and reduces the value of future benefits more than a lower discount rate, which places a greater value on future benefits to society. For more information on discount rates and how EPA uses them in monetizing health benefits, see the User Manual.

In order to run the COBRA model, please select a discount rate to use in this COBRA session.

3%
 7%

Continue

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Step 4: Run the model and review the results



We used AVERT to calculate the emissions reductions due to an increased wind capacity of 1,000 MW.

Annual Emission Reductions (short tons)

Pollutant	Amount
Sulfur Dioxide (SO ₂)	31,739
Nitrogen Oxides (NO _x)	12,788

Note: These reductions are aggregated across all affected states.

* Don't forget to consider the caveats from slides 13 through 15

COBRA (1) converted emissions reductions into air quality improvements, and (2) estimated annual adverse health impacts avoided.

Annual Adverse Health Impacts Avoided

Outcome	Number
Mortality	64 - 145
Asthma Exacerbations	2,020
Heart Attacks	8 - 71
Hospital Admissions	41
Acute Bronchitis	105
Respiratory Symptoms	3,261
Asthma ER Visits	33
Minor Restricted Activity Days	50,320
Work Days Lost	8,460

COBRA monetized the value or benefits of the avoided adverse health effects.

Annual Benefits (2010, \$1,000s)

Dollar Value
\$538,360 - \$1,219,323
\$116
\$945 - \$8,776
\$1,363
\$50
\$91
\$14
\$3,407
\$1,351
total \$545,698 - \$1,234,492

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How Can I Learn More?



Visit Our Website:

<http://www.epa.gov/statelocalclimate/resources/cobra.html>

Contact Us:

Denise Mulholland
EPA State and Local Climate and Energy Programs
(202) 343-9274
Mulholland.Denise@epa.gov



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