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User's Manual for the Co-Benefits Risk Assessment Health Impacts Screening and Mapping Tool (COBRA)

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Developed for
State and Local Energy and Environment Program

State and Local
Energy and Environment Program

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INSTALLATION INSTRUCTIONS

System Requirements

Users must have at least 6 GB free hard drive space, 6+ GB of RAM, i5 processor or AMD equivalent, and Windows 7 or newer. As a general recommendation, COBRA will perform better with a faster processor and a faster hard drive. A SSD drive is preferred. COBRA performance is strongly impacted by hard drive performance. Antivirus programs and full disk encryption programs may negatively impact performance. Typical COBRA run time is 5 to 15 minutes.

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 configuration of your computer, it will take five minutes up 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.

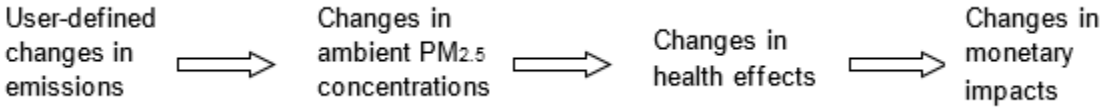
Technical Assistance

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. COBRA also enables advanced users to import their own datasets of emissions inventories, population, incidence, health impact functions, and valuation functions. 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] 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. However, *COBRA is only a screening tool*. More sophisticated, albeit time- and resource-intensive, 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.

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.

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.

The model contains detailed emissions estimates for the years 2017 and 2025. These baseline emissions estimates account for federal and state measures promulgated or under reconsideration by December 2014. The projected EGU emissions include the effects of the Final Mercury and Air Toxics (MATS) rule announced on December 21, 2011 and the Cross-State Air Pollution Rule (CSAPR) issued July 6, 2011. The Clean Power Plan is not included in the 2017 or 2025 baseline emissions cases.[3]

Using COBRA, you can create your own new scenarios by specifying increases or reductions to the baseline emissions estimates for the analysis year. Baseline data is preloaded for analysis years 2017 and 2025, and advanced users can analyze other years by importing custom datasets. 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

[3] More details about the development of the 2017 and 2025 baseline emissions case are available in the Technical Support Document Preparation of Emissions Inventories for the Version 6.2, 2011 Emissions Modeling Platform, available here: https://www.epa.gov/sites/production/files/2015-10/documents/2011v6_2_2017_2025_emismod_tsd_aug2015.pdf

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).[4] 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.

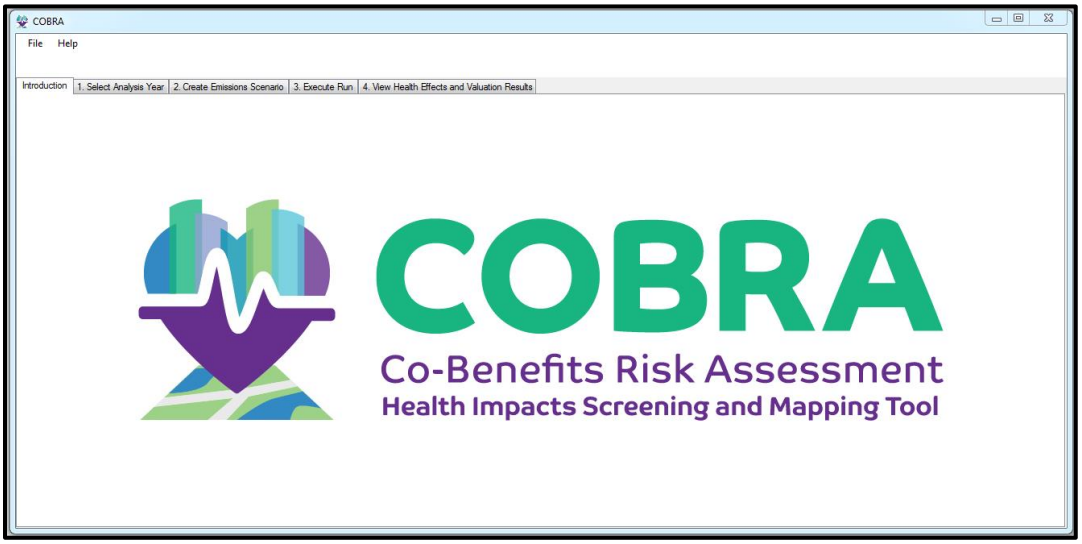
Users can view the results in tabular or map form as well as export the data for use in their own communications.

Overview of Model

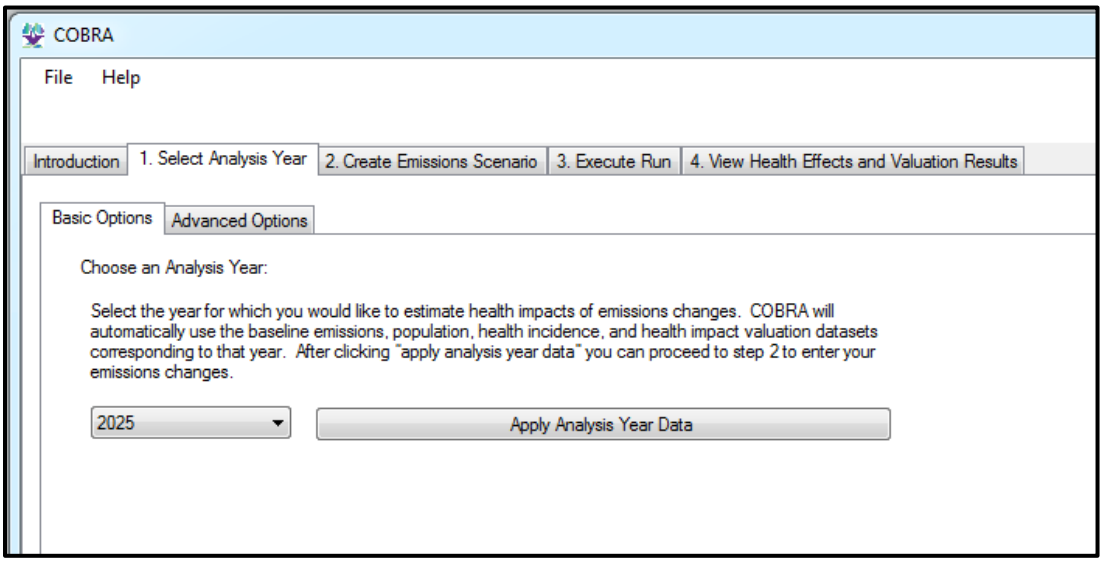
The COBRA screening model is a stand-alone Windows application that contains all of the data needed for the analysis of alternative emissions scenarios; the user is only

[4] 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: https://www.epa.gov/benmap.

required to enter changes in emissions. Upon launching the model, you will see the **Introduction** screen.

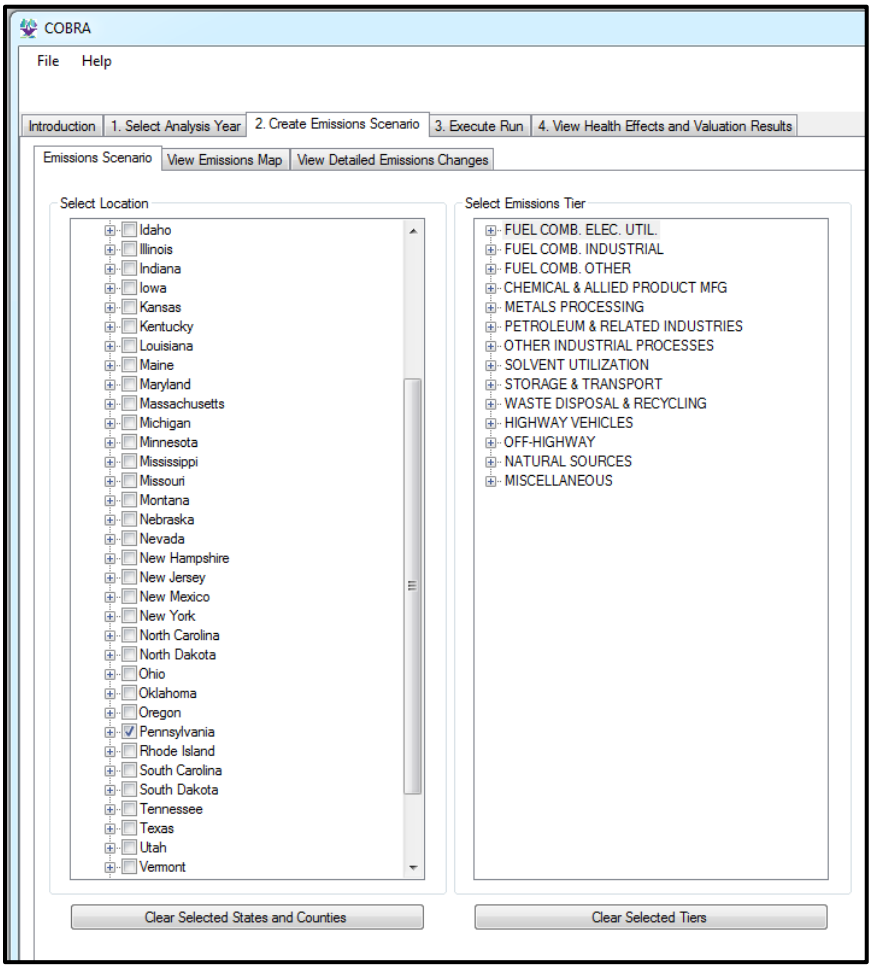


Once you are ready to run a comparison, go to the **1. Select Analysis Year** screen and select the analysis year of interest. Advanced users can load a customized baseline emissions inventory at this stage, which is discussed in more detail in Chapter 3.



Then, go to the **2. Create Emissions Scenario** screen. Use the 'Select Location' panel on the top left of the **Emissions Scenario** tab to indicate the geographic level at which you wish to make your emissions changes. 'US' means that any emissions changes will be applied to all sources in that category throughout the entire U.S. Alternatively, you can enter emissions changes for selected states or selected counties.

Next, select the category of emissions that a policy or action is expected to affect in the 'Select Emissions Tier' panel. 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. COBRA provides three levels of emissions sources (tiers) in a directory tree structure. 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. If you do not know the specific fuel source within the utility category that would be reduced or displaced, you can enter emissions changes at the tier 1 level. For a policy that involves fuel switching or reductions in transportation through vehicle miles traveled, for example, you would select 'HIGHWAY VEHICLES' as the first tier. If you knew the specific fuel (e.g. diesel) that would be reduced, you would select it in the second tier.



Once your geography is determined, you can enter your emissions changes for the nation, a single state, groups of states, a single county, or groups of counties, depending on your previous selection.

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

Online Tool	Description
EPA's Emissions & Generation Resource Integrated Database (eGrid) (https://www.epa.gov/energy/emissions-generation-resource-integrated-database-egrid)	Provides data on the environmental characteristics of electric generation by power plants in the United States.
EPA's AVoided Emissions and geneRation Tool (AVERT) (https://www.epa.gov/statelocalenergy/avoided-emissions-and-generation-tool-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.
EPA's Motor Vehicle Emission Simulator (MOVES) (https://www.epa.gov/moves)	Estimates emissions from mobile sources, including emissions from cars, trucks, and motorcycles.
National Emissions Inventory (https://www.epa.gov/air-emissions-inventories/national-emissions-inventory-nei)	Allows users to view emissions by sector (for 60 emissions inventory sectors) for specific pollutants at varying levels of geographic aggregation.
Power Profiler (https://www.epa.gov/energy/power-profiler)	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 https://www.epa.gov/statelocalenergy/assessing-multiple-benefits-clean-energy-resource-states; 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 https://www.epa.gov/energy-efficiency-and-renewable-energy-sips-and-tips.

Once you have determined the appropriate tier category and location, enter the emission changes for one or more of the five included pollutants in the '2. Create Emissions Scenario' panel at the top right of the COBRA screen. You can enter emissions changes in tons or percentages. Absolute emission reductions in tons can be estimated using a variety of methods. 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 results in reductions in activity levels or emissions from a particular source (or group of sources), 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.[5] On the eGRID website, click on '**eGRID2016 Summary Tables (PDF)**.'[6] Using the Western Electricity Coordinating Council (WECC) Southwest Region (which includes Arizona and New Mexico) as an example, you can obtain the following information:

- Electric Generation: The "Subregion Resource Mix (eGRID 2016)" table on page 3 summarizes electric generation data by region. The net generation for the WECC Southwest Region in 2016 was approximately 166,327,576 megawatt hours (MWh).
- Emissions Rates: The "Subregion Output Emission Rates (eGRID 2016)" table on page 2 provides the WECC Southwest Region's non-baseload output emissions rate for SO_2: 0.4 lbs. per MWh.[7]

If a policy is expected to reduce electric generation by 2% in the WECC Southwest Region, you can calculate the reduction in MWh: 2% × 166,327,576 MWh = 3,326,552 MWh. You can then calculate the emission reductions as:

Emission Reduction = 3,326,552 MWh × 0.4 lbs. SO_2 per MWh = 1,330,621 lbs. SO_2.

This reduction is equal to about 665 tons (1,330,621 lbs. ÷ 2000 lbs. per ton) of SO_2.[8]

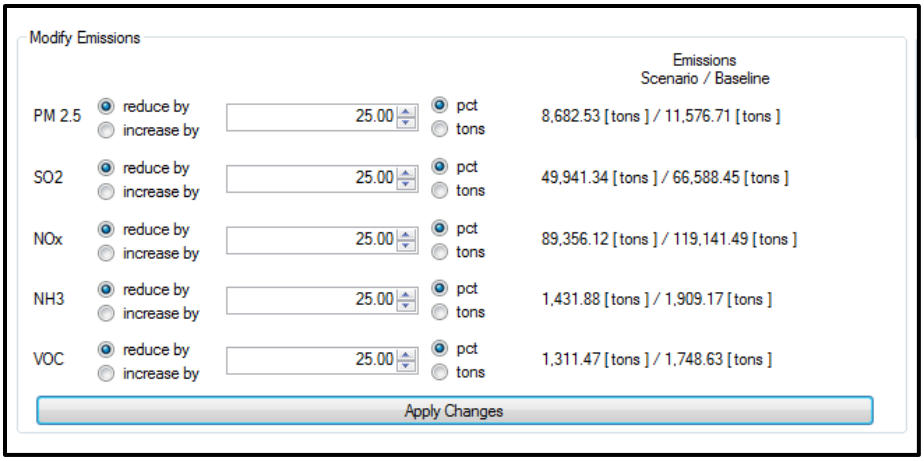
After you have calculated emissions changes, you can enter these changes for as many tier categories as you wish, and you can enter different sets of changes for each state or county (or groups of states and/or counties, if you choose to select more than one). After each change in emissions for a state, county, or group of states or counties, click **Apply Changes**.

[5] While eGRID provides a basic approach for estimating changes in emissions from energy efficiency and renewable energy using annual data, another useful resource available for estimating changes in emissions is EPA's **Avoided Emissions and Generation Tool (AVERT).** AVERT enables users to estimate the regional, state, and county-level emission impacts of different energy efficiency and/or renewable energy programs based on temporal energy savings and hourly generation profiles. For more information or to download AVERT, see: https://www.epa.gov/statelocalenergy/avoided-emissions-and-generation-tool-avert.

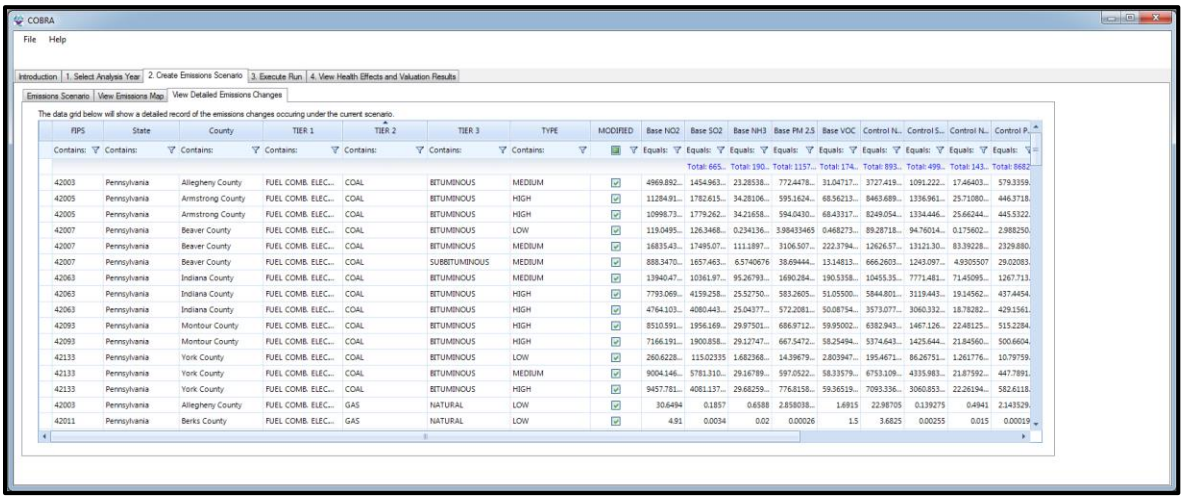
[6] Note that because the latest edition of eGRID was developed using 2016 data, it would be most appropriate to choose the 2017 baseline for the analysis in COBRA.

[7] Non-baseload emissions come from power plants which dispatch to the grid when demand for power exceeds baseload needs (U.S. EPA, 2017).

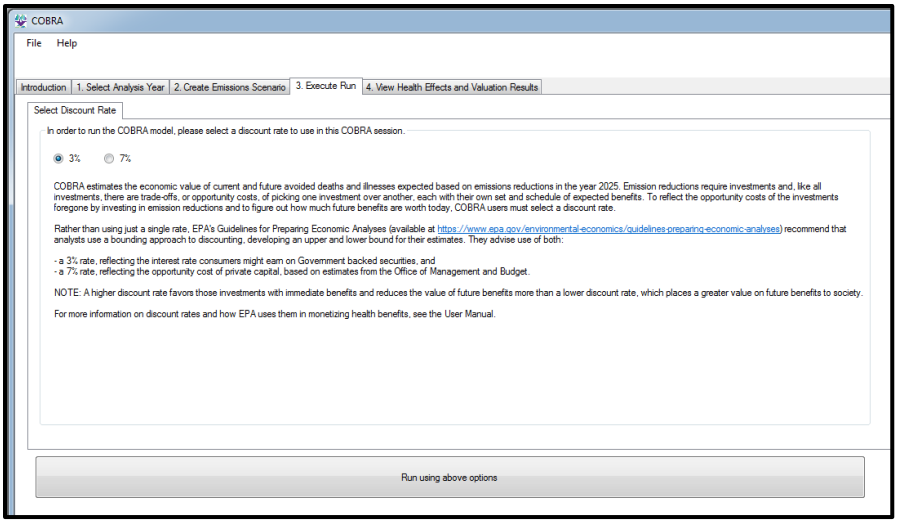
[8] For more information on the benefits of reductions in SO_2 emissions, see EPA's "Assessing the Multiple Benefits of Clean Energy: A Resource for States" report (U.S. EPA, 2011a), available at: https://www.epa.gov/sites/production/files/2015-08/documents/epa_assessing_benefits.pdf.



To review your scenario, click **View Detailed Emissions Changes**.

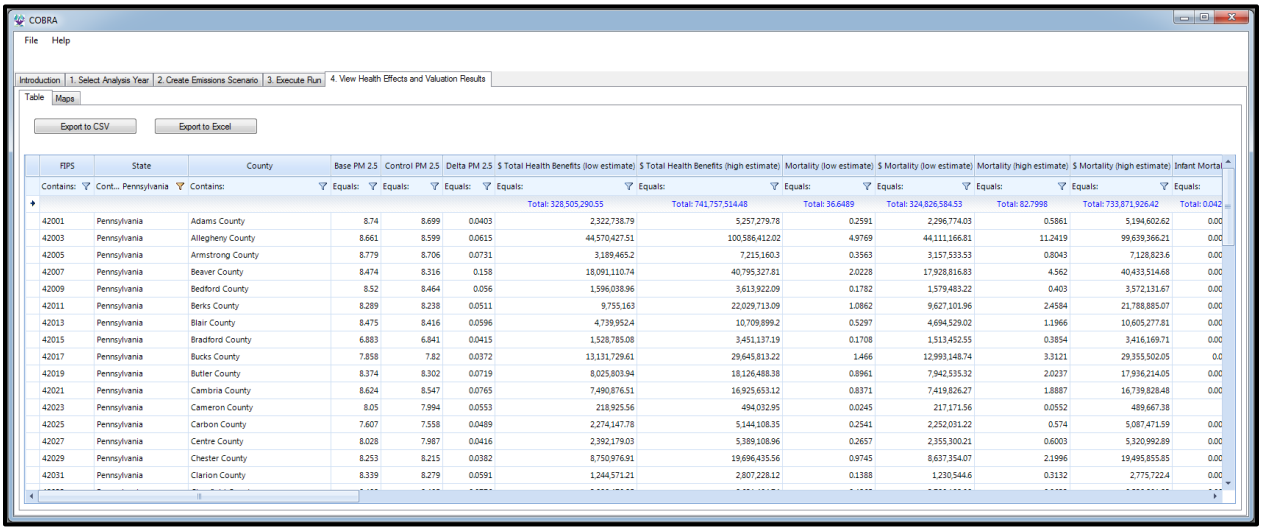


Then, go to the **3. Execute Run** screen to select settings for running your scenario. This tab asks you to choose a discount rate (described in more detail in the Chapter 2 Tutorial). Choose a 3% or 7% discount rate and click **Run using above options** to run the comparison between the scenario you have just created and the baseline scenario.



The model may take 5 to 15 minutes to run, depending on your computer. When the model is done running, you can examine the results in the **4. View Health Effects and Valuation Results** tab. 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 a table (in the **Table** tab) or geographically on a map of the United States (in the **Map** tab).



FIPS	State	County	Base PM 2.5	Control PM 2.5	Delta PM 2.5	$ Total Health Benefits (low estimate)	$ Total Health Benefits (high estimate)	Mortality (low estimate)	$ Mortality (low estimate)	Mortality (high estimate)	$ Mortality (high estimate)	Infant Mortal
Contains:	Cont... Pennsylvania	Contains:	Equals:	Equals:	Equals:	Equals:	Equals:	Equals:	Equals:	Equals:	Equals:	Equals:
						Total: 328,505,290.55	Total: 741,757,514.48	Total: 36.6489	Total: 324,826,584.53	Total: 82.7998	Total: 733,871,926.42	Total: 0.042
42001	Pennsylvania	Adams County	8.74	8.699	0.0403	2,322,738.79	5,257,279.78	0.2591	2,296,774.03	0.5861	5,194,602.62	0.00
42003	Pennsylvania	Allegheny County	8.661	8.599	0.0615	44,570,427.51	100,586,412.02	4.9769	44,111,166.81	11.2419	99,639,366.21	0.00
42005	Pennsylvania	Armstrong County	8.779	8.706	0.0731	3,189,465.2	7,215,160.3	0.3563	3,157,533.53	0.8043	7,128,823.6	0.00
42007	Pennsylvania	Beaver County	8.474	8.316	0.158	18,091,110.74	40,795,327.81	2.0228	17,928,816.83	4.562	40,433,514.68	0.00
42009	Pennsylvania	Bedford County	8.52	8.464	0.056	1,596,038.96	3,613,922.09	0.1782	1,579,483.22	0.403	3,572,131.67	0.00
42011	Pennsylvania	Berks County	8.289	8.238	0.0511	9,755,163	22,029,713.09	1.0862	9,627,101.96	2.4584	21,788,885.07	0.00
42013	Pennsylvania	Blair County	8.475	8.416	0.0596	4,739,952.4	10,709,899.2	0.5297	4,694,529.02	1.1966	10,605,277.81	0.00
42015	Pennsylvania	Bradford County	6.883	6.841	0.0415	1,528,785.08	3,451,137.19	0.1708	1,513,452.55	0.3854	3,416,169.71	0.00
42017	Pennsylvania	Bucks County	7.858	7.82	0.0372	13,131,729.61	29,645,813.22	1.466	12,993,148.74	3.3121	29,355,502.05	0.0
42019	Pennsylvania	Butler County	8.374	8.302	0.0719	8,025,803.94	18,126,488.38	0.8961	7,942,535.32	2.0237	17,936,214.05	0.00
42021	Pennsylvania	Cambria County	8.624	8.547	0.0765	7,490,876.51	16,925,653.12	0.8371	7,419,826.27	1.8887	16,739,828.48	0.00
42023	Pennsylvania	Cameron County	8.05	7.994	0.0553	218,925.56	494,032.95	0.0245	217,171.56	0.0552	489,667.38	
42025	Pennsylvania	Carbon County	7.607	7.558	0.0489	2,274,147.78	5,144,108.35	0.2541	2,252,031.22	0.574	5,087,471.59	0.00
42027	Pennsylvania	Centre County	8.028	7.987	0.0416	2,392,179.03	5,389,108.96	0.2657	2,355,300.21	0.6003	5,320,992.89	0.00
42029	Pennsylvania	Chester County	8.253	8.215	0.0382	8,750,976.91	19,696,435.56	0.9745	8,637,354.07	2.1996	19,495,855.85	0.00
42031	Pennsylvania	Clarion County	8.339	8.279	0.0591	1,244,571.21	2,807,228.12	0.1388	1,230,544.6	0.3132	2,775,722.4	0.00

$ Nonfatal Heart Attacks (low estimate)	Nonfatal Heart Attacks (high estimate)	$ Nonfatal Heart Attacks (high estimate	Emergency Room Visits, Asthma	$ Emergency Room Visits, Asthma
Equals:	Equals:	Equals:	Equals:	Equals:
Total: 507,695.8	Total: 40.1716	Total: 4,714,577.84	Total: 17.7523	Total: 7,564.73
4,429.62	0.3475	41,142.0	0.1286	54.8
58,869.39	4.6808	546,654.5	2.2255	948.36
6,566.95	0.5249	60,971.9	0.1372	58.47
24,106.98	1.9117	223,626.	0.7422	316.28
3,045.32	0.2454	28,280.0	0.0771	32.87
13,607.79	1.048	126,374.7	0.7164	305.26
7,144.29	0.5685	66,342.2	0.2134	90.95
2,369.12	0.187	22,004.0	0.0727	30.96
18,306.6	1.4486	170,036.5	0.6929	295.26
12,915.85	1.0277	119,921.56	0.3809	162.29
13,854.39	1.1376	128,628.75	0.2972	126.66
315.16	0.0269	2,926.7	0.0072	3.07
4,165.54	0.3256	38,685.7	0.0955	40.71
3,769.03	0.2932	35,006.2	0.1999	85.18
10,491.65	0.8295	97,448.5	0.6138	261.57
2,109.45	0.1675	19,588.5	0.0678	28.9
6,376.67	0.4937	59,202.5	0.1751	74.63
1,476.21	0.115	13,710.1	0.0552	23.52
3,224.31	0.2559	29,946.9	0.0834	35.54
1,823.58	0.1431	16,940.	0.0526	22.42
8,518.74	0.6807	79,118.4	0.3233	137.75
9,625.52	0.7622	89,395.	0.4034	171.88
13,654.82	1.0585	126,832.47	0.6279	267.58
2,033.46	0.1606	18,885.1	0.0379	16.14

The results table includes a row with blue text that summarizes the total impact of the scenario. To view the impact of the scenario on a specific state, filter the "state" column for the state of interest. For example, results in the table above show estimated impacts of the scenario for Pennsylvania. According to these results, the emissions reductions in 2025 would result in the following health effects in Pennsylvania:

- 36.6 to 82.8 avoided premature adult deaths (over the next 20 years), valued at an estimated $324 and $734 million;
- 4.3 to 40.2 avoided nonfatal heart attacks (in 2025), valued at an estimated $508,000, to $4,710,000 and
- 17.8 avoided asthma emergency room visits (in 2025), valued at an estimated $7,560.

Note that health effects are not necessarily whole numbers. This is because COBRA calculates small statistical risk reductions which are then aggregated over the population. For example, if 150,000 people experience a 0.001% reduction in mortality risk, this would be reported as 1.5 "statistical lives saved." This statistical life and its associated monetary value represents the sum of many small risk reductions and does not correspond to the loss or value of an individual life. Users may want to round these values to the nearest whole before presenting the results.

Result sets can be exported for use in outside programs and presentations. To save your results in a table form, click on **Export to CSV** or **Export to Excel** (depending on your preferred format) in the **Table** tab. To save your results in map form, navigate to the **Map** tab, right click on the data in the 'Legend' panel, then click **Data…Export Data**.

Caveats and Limitations

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

- *Determination of attainment.* Modeling the attainment of National Ambient Air Quality Standards (NAAQS) requires more sophisticated air quality modeling than that currently built into COBRA.
- *Estimating dynamic market effects.* COBRA does not account for changes in emissions that can result from changes in electricity market responses to policy. For example, emissions in some states and regions are "capped" by laws or regulations and emission allowances can then be traded across entities within a capped region. In these regions, a reduction in emissions in one location *may* result in an increase (rebound) in emissions in another area subject to the cap. COBRA does not automatically capture these types of potential effects in electricity market dispatch, so care should be exercised when interpreting COBRA results 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 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. Subsequent chapters provide more detailed information on each step, and describe additional options you can use for more complex analyses.

Chapter 3 describes the process of selecting and exploring baseline data.

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 and save your results.

Chapter 6 explains how to use COBRA's mapping functionality.

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 functions used 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 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.** Explains how to run sample COBRA scenarios.
- **Appendix H: Instructions for Batch Functionality.** Explains how to run multiple COBRA scenarios in batch mode.
- **Appendix I: 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. As described in the text box below, COBRA v3.1 also includes more advanced options for users who want to change underlying assumptions (e.g. population, emissions baseline). Subsequent chapters describe how to use the more advanced features.

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, you 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 business-as-usual? This tutorial will show you how to use COBRA to examine this type of scenario through the following steps:

Step 1. Select the analysis year and view the baseline emissions data.

Step 2. Select the geography and tier category for emissions changes and define the emissions changes

Step 3. Select a discount rate and run the comparison.

Step 4. View and save your results.

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

Compared to previous versions, COBRA (3.0) offers additional functionality and flexibility for advanced users, while still being easy to operate for basic analyses. The table below compares COBRA's advanced options to the simpler, quick-start options. More advanced options will be discussed in subsequent chapters.

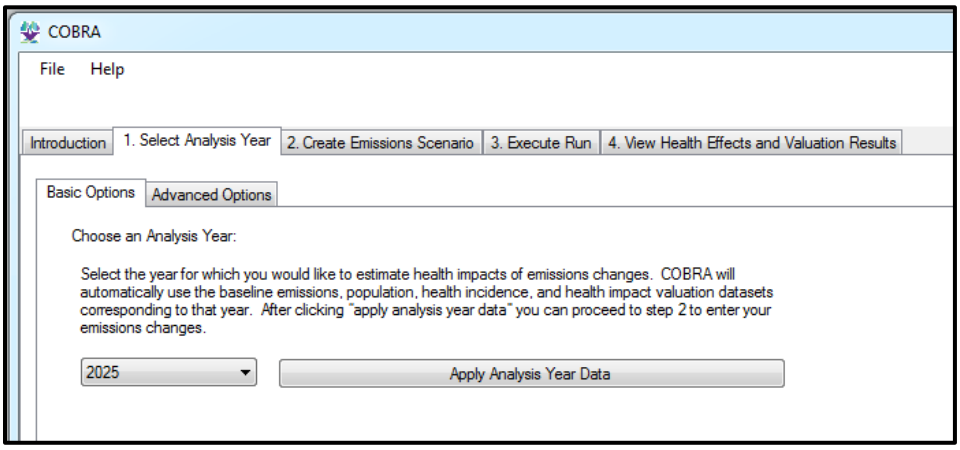
Quick-Start Options	Advanced Options
Preloaded 2017 and 2025 emissions baseline	Custom emissions baseline
Preloaded 2017 and 2025 incidence data	Custom incidence data
Preloaded 2017 and 2025 population data	Custom population data
Preloaded health effect functions	Custom health effect functions
Preloaded 2017 and 2025 valuation functions	Custom valuation functions
Enter emissions scenario in user interface	Upload custom emissions scenario
Run COBRA separately for each emissions scenario	Run multiple emissions scenarios in batch mode
View default map output in COBRA	Customize map appearance and export for further manipulation or analysis in other tools

To open COBRA, click **Start**… **All Programs**… **COBRA**… **COBRA** The model will open and COBRA will display the main screen. You will see five tabs at the very top: **Introduction, 1. Select Analysis Year, 2. Create**

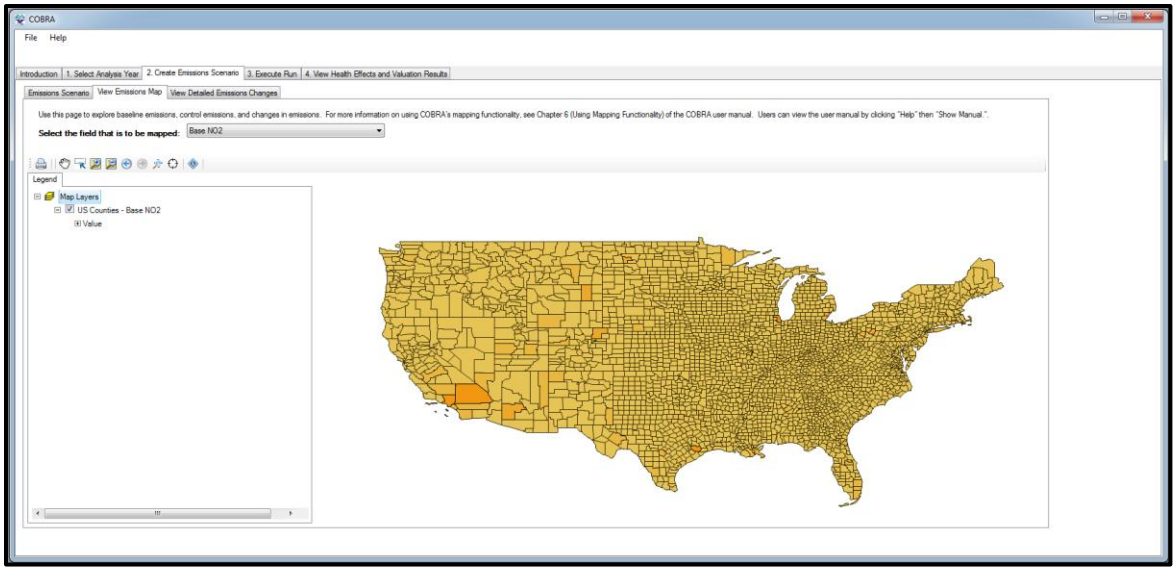
Emissions Scenario, 3. Execute Run and **4. View Health Effects and Valuation Results**. Below, we provide detailed descriptions of the steps needed to run a scenario.

Step 1. Select the baseline data.

Click **1. Select Analysis Year** and you will see two tabs: **Basic Options** and **Advanced Options**. To do a basic screening analysis for analysis year 2025, select "2025" in the drop down menu and click **Apply selected analysis year** in the **Basic Options** tab.

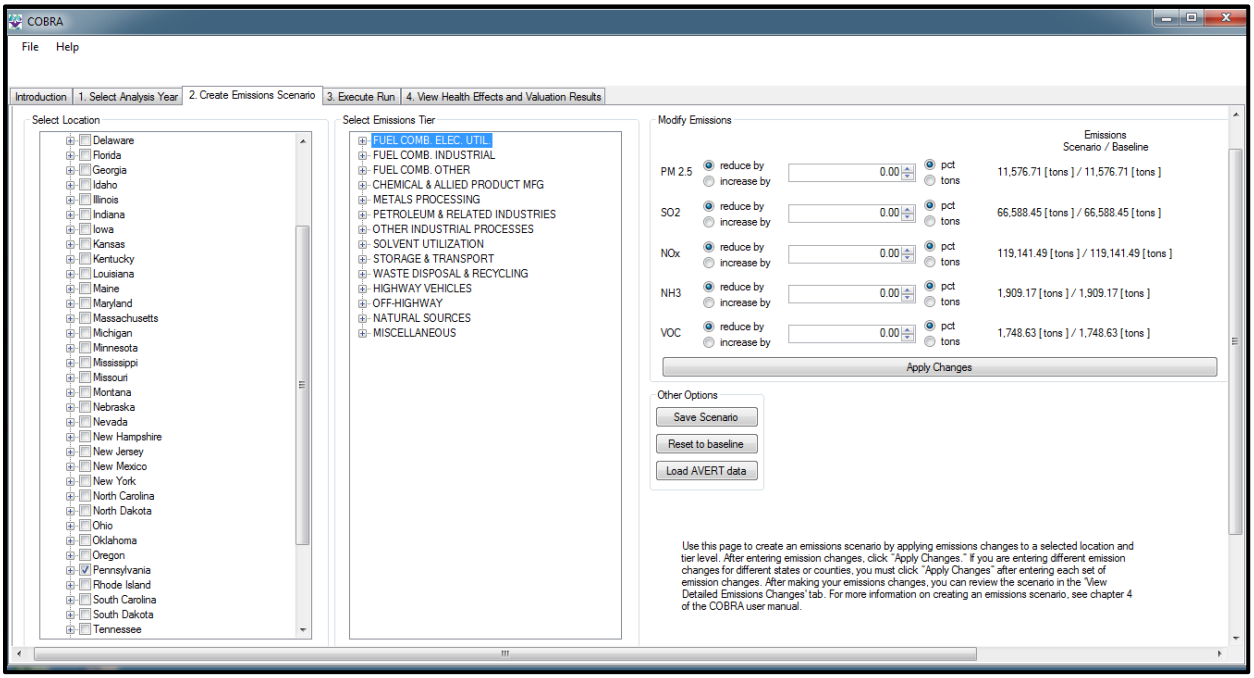


To explore the preloaded baseline emissions data, go to the **2. Create Emissions Scenario** tab. On the top of this screen you will see three tabs: **Emissions Scenario**, **View Emissions Map**, and **View Detailed Emissions Changes**. Click on the **View Emissions Map** tab. At the top of this screen, you will see a drop-down menu labeled 'Select the field that is to be mapped.' The first five options listed (Base NH3, Base NO2, Base PM2.5, Base SO2, and Base VOC) correspond to the baseline emissions of ammonia (NH_3), nitrogen oxides (NO_x), fine particulate matter ($PM_{2.5}$), sulfur dioxide (SO_2), and volatile organic compounds (VOCs), respectively, from all sectors. Select any of these emissions to view a map of county-level baseline emissions. See Chapter 6 for more details on how to use COBRA's mapping functionality.



Step 2. Define the emissions changes and 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. Click on the **2. Create Emissions Scenario** tab. On the top of this screen you will see three tabs: **Emissions Scenario**, **View Emissions Map**, and **View Detailed Emissions Changes.** Click on the **Emissions Scenario** tab.



In the top left panel you can 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 the $PM_{2.5}$ reductions and health benefits of a defined scenario). Since this example only analyzes changes statewide in Pennsylvania, check the box next to 'Pennsylvania' in the list.

If you wanted to vary the emissions changes across counties, or only make changes in some counties, you could click the '+' button next to Pennsylvania and enter different emissions changes for each county. 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 you are looking at a statewide change.

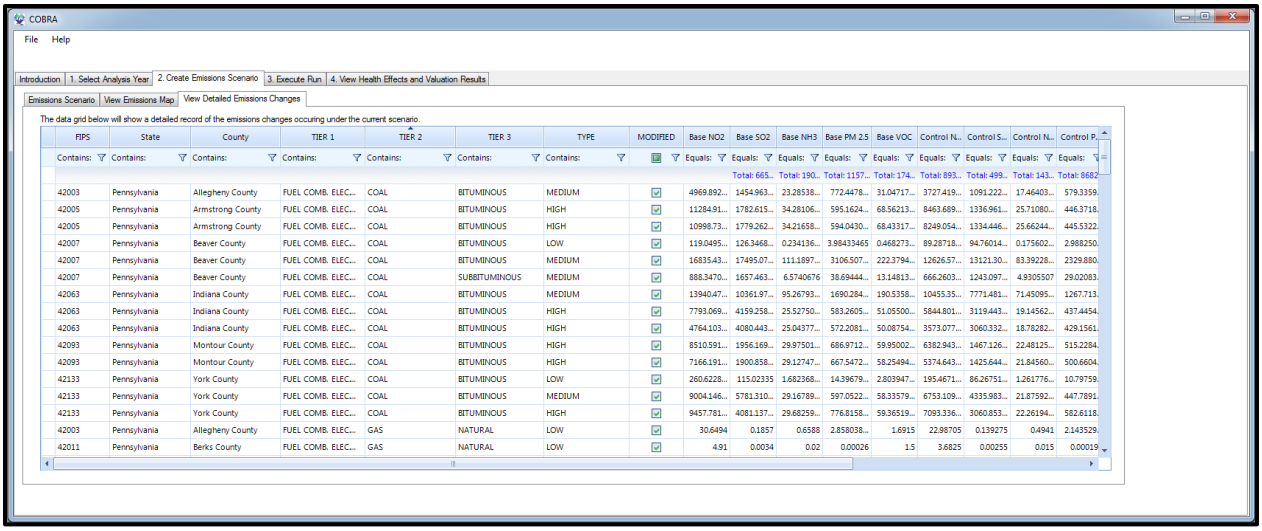
The next step is to define the categories of emissions affected. The middle panel contains a directory tree with all the tier 1, 2, and 3 source categories (see Appendix A for a list of source categories and their emissions). You can define emissions changes at any level, but each level always includes all the levels indented underneath it. In this example, you want to change all of the source categories that are electrical utilities, so click 'FUEL COMB. ELEC. UTIL.'

The panel on the right-hand side of the screen lists each pollutant included in the model. Since this scenario reduces all baseline emissions by 25 percent, type '25' in the box next to each pollutant. The default selections are 'reduce by' and 'percent'; leave them as they are. Chapter 4 describes how to create more sophisticated emissions scenarios, such as scenarios that cover multiple geographies or involve different emissions changes for different pollutants. Click **Apply Changes** to save your changes. The changes apply to all the locations selected.

If you wanted to enter additional emission changes in another location, you would click **Clear Selected States and Countries**, then repeat the process of selecting a new geographic location tier and entering the emission change for that location. You must click **Apply Changes** after entering emissions changes for each location. If you make a mistake or want to start over, click the **Reset to Baseline** button, which will erase all entries. In this example, we are running the analysis for a single scenario affecting only one state, so we will proceed without applying any additional emissions changes.

NOTE: Users of EPA's AVERT model can upload the emissions changes quantified in AVERT into COBRA so that the user does not have to enter all the changes manually. Chapter 4 describes the process for uploading AVERT outputs as COBRA inputs.

You can review your emissions scenario in table form by clicking the **View Detailed Emissions Changes** tab or in map form by clicking the **View Emissions Map** tab.



FIPS	State	County	TIER 1	TIER 2	TIER 3	TYPE	MODIFIED	Base NO2	Base SO2	Base NH3	Base PM 2.5	Base VOC	Control N...	Control S...	Control N...	Control P...
Contains:	Contains:	Contains:	Contains:	Contains:	Contains:	Contains:		Equals:	Equals:	Equals:	Equals:	Equals:	Equals:	Equals:	Equals:	Equals:
									Total: 665...	Total: 190...	Total: 1157...	Total: 174...	Total: 893...	Total: 499...	Total: 143...	Total: 8682
42003	Pennsylvania	Allegheny County	FUEL COMB. ELEC...	COAL	BITUMINOUS	MEDIUM	☑	4969.892...	1454.963...	23.28538...	772.4478...	31.04717...	3727.419...	1091.222...	17.46403...	579.3359
42005	Pennsylvania	Armstrong County	FUEL COMB. ELEC...	COAL	BITUMINOUS	HIGH	☑	11284.91...	1782.615...	34.28106...	595.1624...	68.56213...	8463.689...	1336.961...	25.71080...	446.3718
42005	Pennsylvania	Armstrong County	FUEL COMB. ELEC...	COAL	BITUMINOUS	HIGH	☑	10998.73...	1779.262...	34.21658...	594.0430...	68.43317...	8249.054...	1334.446...	25.66244...	445.5322
42007	Pennsylvania	Beaver County	FUEL COMB. ELEC...	COAL	BITUMINOUS	LOW	☑	119.0495...	126.3468...	0.234136...	3.98433465	0.468273...	89.28718...	94.76014...	0.175602...	2.988250
42007	Pennsylvania	Beaver County	FUEL COMB. ELEC...	COAL	BITUMINOUS	MEDIUM	☑	16835.43...	17495.07...	111.1897...	3106.507...	222.3794...	12626.57...	13121.30...	83.39228...	2329.880
42007	Pennsylvania	Beaver County	FUEL COMB. ELEC...	COAL	SUBBITUMINOUS	MEDIUM	☑	888.3470...	1657.463...	6.5740676	38.69444...	13.14813...	666.2603...	1243.097...	4.9305507	29.02083
42063	Pennsylvania	Indiana County	FUEL COMB. ELEC...	COAL	BITUMINOUS	MEDIUM	☑	13940.47...	10361.97...	95.26793...	1690.284...	190.5358...	10455.35...	7771.481...	71.45095...	1267.713
42063	Pennsylvania	Indiana County	FUEL COMB. ELEC...	COAL	BITUMINOUS	HIGH	☑	7793.069...	4159.258...	25.52750...	583.2605...	51.05500...	5844.801...	3119.443...	19.14562...	437.4454
42063	Pennsylvania	Indiana County	FUEL COMB. ELEC...	COAL	BITUMINOUS	HIGH	☑	4764.103...	4080.443...	25.04377...	572.2081...	50.08754...	3573.077...	3060.332...	18.78282...	429.1561
42093	Pennsylvania	Montour County	FUEL COMB. ELEC...	COAL	BITUMINOUS	HIGH	☑	8510.591...	1956.169...	29.97501...	686.9712...	59.95002...	6382.943...	1467.126...	22.48125...	515.2284
42093	Pennsylvania	Montour County	FUEL COMB. ELEC...	COAL	BITUMINOUS	HIGH	☑	7166.191...	1900.858...	29.12747...	667.5472...	58.25494...	5374.643...	1425.644...	21.84560...	500.6604
42133	Pennsylvania	York County	FUEL COMB. ELEC...	COAL	BITUMINOUS	LOW	☑	260.6228...	115.02335	1.682368...	14.39679...	2.803947...	195.4671...	86.26751...	1.261776...	10.79759
42133	Pennsylvania	York County	FUEL COMB. ELEC...	COAL	BITUMINOUS	MEDIUM	☑	9004.146...	5781.310...	29.16789...	597.0522...	58.33579...	6753.109...	4335.983...	21.87592...	447.7891
42133	Pennsylvania	York County	FUEL COMB. ELEC...	COAL	BITUMINOUS	HIGH	☑	9457.781...	4081.137...	29.68259...	776.8158...	59.36519...	7093.336...	3060.853...	22.26194...	582.6118
42003	Pennsylvania	Allegheny County	FUEL COMB. ELEC...	GAS	NATURAL	LOW	☑	30.6494	0.1857	0.6588	2.858038...	1.6915	22.98705	0.139275	0.4941	2.143529
42011	Pennsylvania	Berks County	FUEL COMB. ELEC...	GAS	NATURAL	LOW	☑	4.91	0.0034	0.02	0.00026	1.5	3.6825	0.00255	0.015	0.00019

Step 3. Run the scenario.

Next, go to the **3. Execute Run** tab. This tab asks 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). Therefore, COBRA accounts for this 'time value of money' preference (i.e., a general preference for receiving benefits now rather than later) by discounting benefits received later. 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 3% and 7% 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, you will use a 3% discount rate. Click **Run using above options**.

> **NOTE:** COBRA may take 5 to 15 minutes to run, and COBRA may be "not responding" as it runs. The run time depends on your computer.

Step 4. View and save the results.

View the results

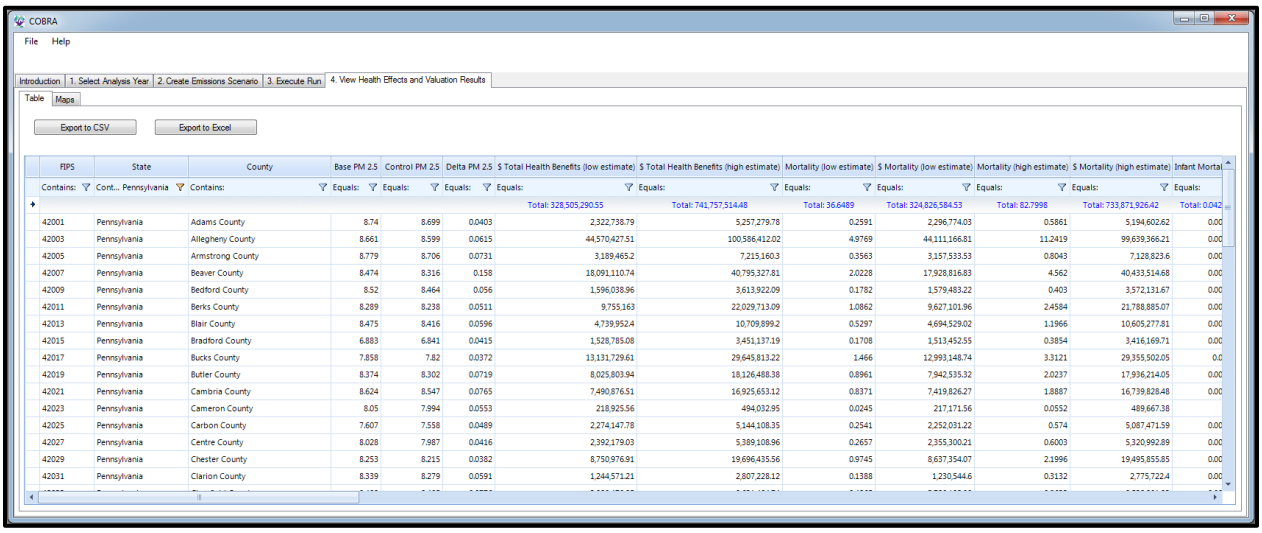
Once your run is complete, COBRA will automatically navigate to the last tab, **4. View Health Effects and Valuation Results**. You will see a screen with two tabs at the top: **Table** and **Map**.

Click on the first tab, **Table**. This tab shows the changes in air quality and reductions in health effects associated with your scenario. The air quality variables shown are 'Base PM 2.5', 'Control PM 2.5,' and 'Delta PM 2.5.' Delta PM2.5 is the difference in ambient

fine particulate matter ($PM_{2.5}$) between the baseline scenario and your new scenario (the control scenario) in the year of your analysis (in this example, 2025). Note that positive values indicate a reduction in $PM_{2.5}$ in the control scenario.

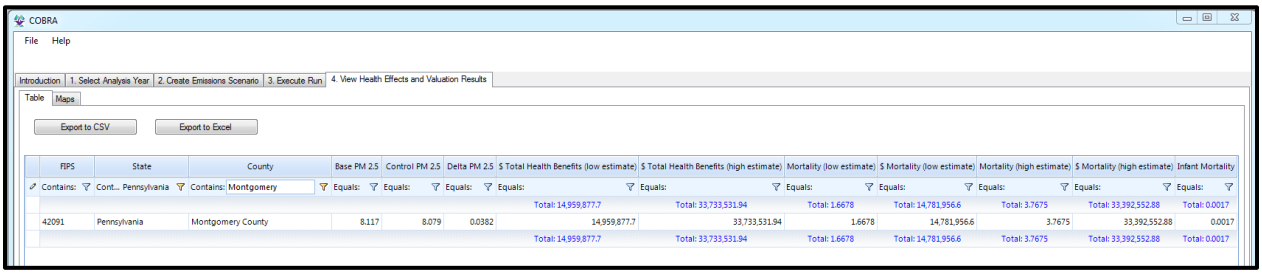
To the right, this table also shows the reductions in health effects associated with changes in air quality and the dollar values associated with those reductions. Note that positive values indicate a decrease in impacts (that is, fewer cases of illness/premature mortality or avoided economic loss).

The default view shows the whole country, but since the majority of the air quality changes are expected to be in Pennsylvania, filter the state by clicking on the arrow next to 'State' and clicking 'Pennsylvania' from the drop-down list.



FIPS	State	County	Base PM 2.5	Control PM 2.5	Delta PM 2.5	$ Total Health Benefits (low estimate)	$ Total Health Benefits (high estimate)	Mortality (low estimate)	$ Mortality (low estimate)	Mortality (high estimate)	$ Mortality (high estimate)	Infant Mortal
Contains:	Cont... Pennsylvania	Contains:	Equals:	Equals:	Equals:	Equals:	Equals:	Equals:	Equals:	Equals:	Equals:	Equals:
						Total: 328,505,290.55	Total: 741,757,514.48	Total: 36.6489	Total: 324,826,584.53	Total: 82.7998	Total: 733,871,926.42	Total: 0.042
42001	Pennsylvania	Adams County	8.74	8.699	0.0403	2,322,738.79	5,257,279.78	0.2591	2,296,774.03	0.5861	5,194,602.62	0.00
42003	Pennsylvania	Allegheny County	8.661	8.599	0.0615	44,570,427.51	100,586,412.02	4.9769	44,111,166.81	11.2419	99,639,366.21	0.00
42005	Pennsylvania	Armstrong County	8.779	8.706	0.0731	3,189,465.2	7,215,160.3	0.3563	3,157,533.53	0.8043	7,128,823.6	0.00
42007	Pennsylvania	Beaver County	8.474	8.316	0.158	18,091,110.74	40,795,327.81	2.0228	17,928,816.83	4.562	40,433,514.68	0.00
42009	Pennsylvania	Bedford County	8.52	8.464	0.056	1,596,038.96	3,613,922.09	0.1782	1,579,483.22	0.403	3,572,131.67	0.00
42011	Pennsylvania	Berks County	8.289	8.238	0.0511	9,755,163	22,029,713.09	1.0862	9,627,101.96	2.4584	21,788,885.07	0.00
42013	Pennsylvania	Blair County	8.475	8.416	0.0596	4,739,952.4	10,709,899.2	0.5297	4,694,529.02	1.1966	10,605,277.81	0.00
42015	Pennsylvania	Bradford County	6.883	6.841	0.0415	1,528,785.08	3,451,137.19	0.1708	1,513,452.55	0.3854	3,416,169.71	0.00
42017	Pennsylvania	Bucks County	7.858	7.82	0.0372	13,131,729.61	29,645,813.22	1.466	12,993,148.74	3.3121	29,355,502.05	0.0
42019	Pennsylvania	Butler County	8.374	8.302	0.0719	8,025,803.94	18,126,488.38	0.8961	7,942,535.32	2.0237	17,936,214.05	0.00
42021	Pennsylvania	Cambria County	8.624	8.547	0.0765	7,490,876.51	16,925,653.12	0.8371	7,419,826.27	1.8887	16,739,828.48	0.00
42023	Pennsylvania	Cameron County	8.05	7.994	0.0553	218,925.56	494,032.95	0.0245	217,171.56	0.0552	489,667.38	
42025	Pennsylvania	Carbon County	7.607	7.558	0.0489	2,274,147.78	5,144,108.35	0.2541	2,252,031.22	0.574	5,087,471.59	0.00
42027	Pennsylvania	Centre County	8.028	7.987	0.0416	2,392,179.03	5,389,108.96	0.2657	2,355,300.21	0.6003	5,320,992.89	0.00
42029	Pennsylvania	Chester County	8.253	8.215	0.0382	8,750,976.91	19,696,435.56	0.9745	8,637,354.07	2.1996	19,495,855.85	0.00
42031	Pennsylvania	Clarion County	8.339	8.279	0.0591	1,244,571.21	2,807,228.12	0.1388	1,230,544.6	0.3132	2,775,722.4	0.00

Here, you see that the emissions scenario results in an estimated 36.6 to 82.8 adult premature deaths avoided and 17.8 avoided emergency room visits for asthma. You can also look at a specific county in Pennsylvania. To do this, filter the county level by clicking on the arrow next to 'County' and selecting the county name. For this example, you will select 'Montgomery County' from the drop-down list.



FIPS	State	County	Base PM 2.5	Control PM 2.5	Delta PM 2.5	$ Total Health Benefits (low estimate)	$ Total Health Benefits (high estimate)	Mortality (low estimate)	$ Mortality (low estimate)	Mortality (high estimate)	$ Mortality (high estimate)	Infant Mortality
Contains:	Cont... Pennsylvania	Contains: Montgomery	Equals:	Equals:	Equals:	Equals:	Equals:	Equals:	Equals:	Equals:	Equals:	Equals:
						Total: 14,959,877.7	Total: 33,733,531.94	Total: 1.6678	Total: 14,781,956.6	Total: 3.7675	Total: 33,392,552.88	Total: 0.0017
42091	Pennsylvania	Montgomery County	8.117	8.079	0.0382	14,959,877.7	33,733,531.94	1.6678	14,781,956.6	3.7675	33,392,552.88	0.0017
						Total: 14,959,877.7	Total: 33,733,531.94	Total: 1.6678	Total: 14,781,956.6	Total: 3.7675	Total: 33,392,552.88	Total: 0.0017

You will see that in Montgomery County, the estimated ambient $PM_{2.5}$ concentration in the control scenario is 8.079μg/m^3, compared to the estimated baseline concentration of 8.117 μg/m^3. The difference between the two estimated concentrations (Delta $PM_{2.5}$) is 0.038 μg/m^3, 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 and in other counties). Note that positive changes indicate a lower concentration in the control scenario. If the value in 'Delta $PM_{2.5}$' were negative, it would indicate an increase in concentration. In this county, the emissions reduction scenario results in an estimated 1.7 to 3.8 adult premature deaths avoided (over the next 20 years), an estimated 0.2 to 1.6 avoided non-fatal heart attacks, and an estimated 1.0 avoided emergency room visit for asthma (in 2025).

The table includes low and high estimates for the changes in the number of cases and the corresponding economic values for adult mortality and non-fatal heart attacks. 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.

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

- **Emergency Room Visits for Asthma.** In COBRA, most health effects and their economic values are expected to occur in the year of analysis. For instance, this scenario results in less than one avoided emergency room visits for asthma in Montgomery County. This fraction of an avoided case and its economic value (approximately $410) would occur in 2025.

- **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 1.7 avoided cases of adult mortality are valued at a total of approximately $15 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 this scenario results in a range of 0.2 to 1.6 cases of non-fatal

heart attacks in 2025, all economic benefits associated with this change ($20,000 to $180,000) would not accrue in that same year.

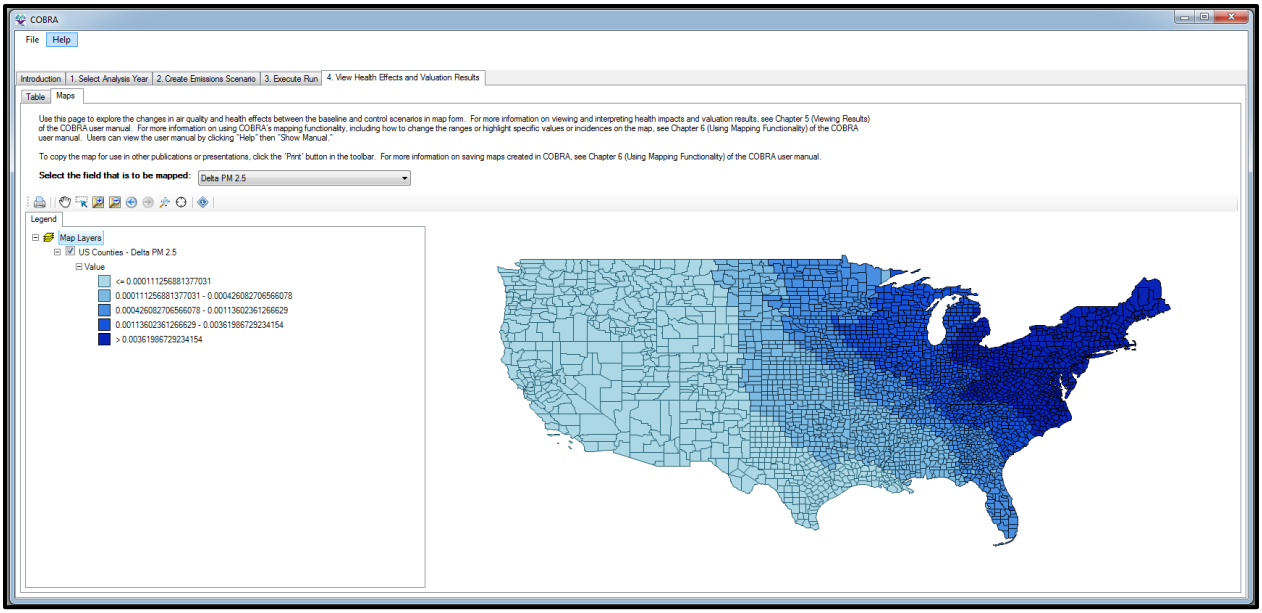
The table below relates the timing of the expected health effects and economic costs or benefits to the specific types of incidences in COBRA.

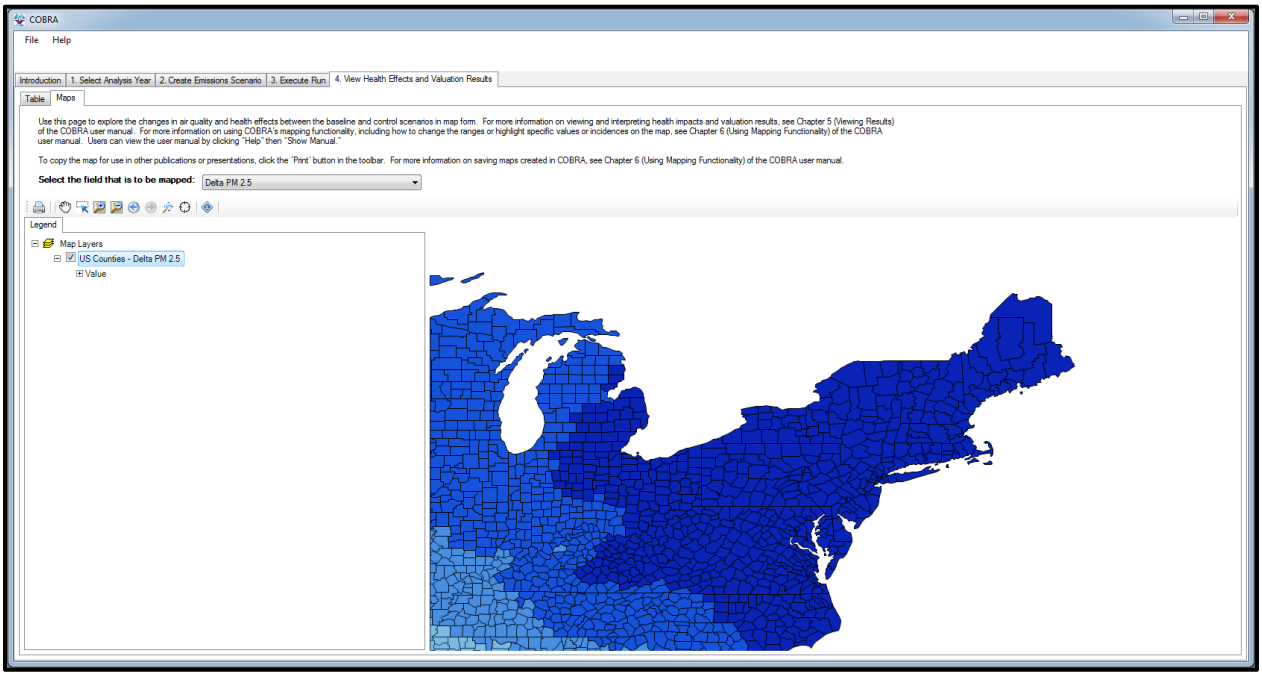
Type of Health Incidence	All health effects occur in the year of analysis?	All economic costs or benefits occur in same year of analysis?
Adult mortality	No	No, the value is discounted to present terms
Non-fatal heart attacks	Yes	No, the value is discounted to present terms
All other health impacts	Yes	Yes

In addition, remember that although emissions were changed only in Pennsylvania, COBRA calculates changes in $PM_{2.5}$ for the whole country. If you would like to examine the results for any of states bordering Pennsylvania, simply filter for different states.

As described earlier, it is also important to remember COBRA does not capture dynamic effects of electricity markets – these markets determine electricity dispatch by EGUs and associated emissions levels. For example, if you assume an emission reduction among power plants in one area, it is possible that electricity generation and emissions may increase in another location unless there is an underlying change in electricity demand. Because COBRA does not capture potential electricity market effects, users should exercise care when interpreting the impacts of an emissions change in a specific location.

The **Map** tab shows the results from the previous table on a map. When you click on the tab you will see a map of the United States. To display a result, select an outcome from the drop-down menu labeled 'Select the field that is to be mapped.' Below, the map of Delta $PM_{2.5}$ shows 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 selecting them from the drop-down list under 'Select the field that is to be mapped'. See Chapter 6 for more details on how to use COBRA's mapping functionality.





Export and save your results.

You may want to look at and manipulate the results data outside of COBRA. You can export data sets into a CSV format, which can be used with spreadsheet programs.

Emissions Scenario Definition in Table Form

To save the definition of your emissions changes scenario go to the **2. Create Emissions Scenario** tab. In the top right panel, click **Save Scenario**. In the following window, browse to the file location where you want to save your data, and select 'CSV files' in the

‘Save as type’ drop-down box. You can then enter a name for the file in the box above. Click **Save** and COBRA will save the file.

Results in Table Form

To export the results table, go to the **4. View Health Effects and Valuation Results** tab and then to the **Table** tab. Click on the **Export to CSV** or **Export to Excel** button, depending on your preferred format. In the following window, browse to the file location where you want to save your data, enter a name for the file, and click **Save**.

Results in Map Form

To save a map for use in another mapping application, navigate to the map and right-click on the ‘US counties’ data in the legend panel and then click **Data… Export Data**. In the following window, browse to the file location where you want to save your data, enter a file name, and select ‘.shp’ in the ‘Save as type:’ drop-down menu. Click **Save** and COBRA will save the file.

To save the map as an image, click the ‘Print’ button in the toolbar. In the following window, click **File… Save**. Then browse to the file location where you want to save your data and select ‘DotSpatial Layout File’ or ‘Portable Network Graphics’ in the ‘Save as type’ drop-down box. You can then enter a name for the file in the box above (e.g., type ‘Penn Utility Reduction 2025 - 3%’). Click **Save** and COBRA will save the file.

CHAPTER 3. Baseline Data

Click on the **1. Select Analysis Year** tab to select an analysis year.

Basic Options

The COBRA model contains detailed 2017 and 2025 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 baseline data). It is recommended that new COBRA users start by using the default 2017 and 2025 baseline emissions database. To use the 2025 default emissions, go to the **Basic Options** tab, select 2025 in the "Select analysis year" drop down menu, and click **Apply selected analysis year**. COBRA will automatically use the population, baseline health incidence, baseline emissions, and health impact valuation datasets that correspond to the analysis year you select.

Advanced Options

Users can also import custom datasets for population, baseline health incidence, baseline emissions, health effect functions, and health impact valuation.

Custom Baseline Emissions

There are two ways for users to import custom emissions: (1) load a file containing only baseline emissions or (2) load a file containing emissions for both the baseline and your control scenario. It is important for input files to correspond to the same year, so if you choose to import custom baseline emissions data for a year that is not preloaded, you would also want to modify population data and incidence data to represent that same year. For example, running COBRA with a 2025 baseline emissions inventory, 2025 population data, and 2025 incidence data would result in COBRA estimating 2025 health benefits. However, running COBRA with a 2010 baseline emissions inventory and 2025 population and incidence data would result in theoretical annual health benefits that do not correspond to any calendar year. Alternatively, running COBRA with a projected emissions inventory for 2030 and the default 2025 population and incidence data would assume that population and incidence are constant from 2025 to 2030.

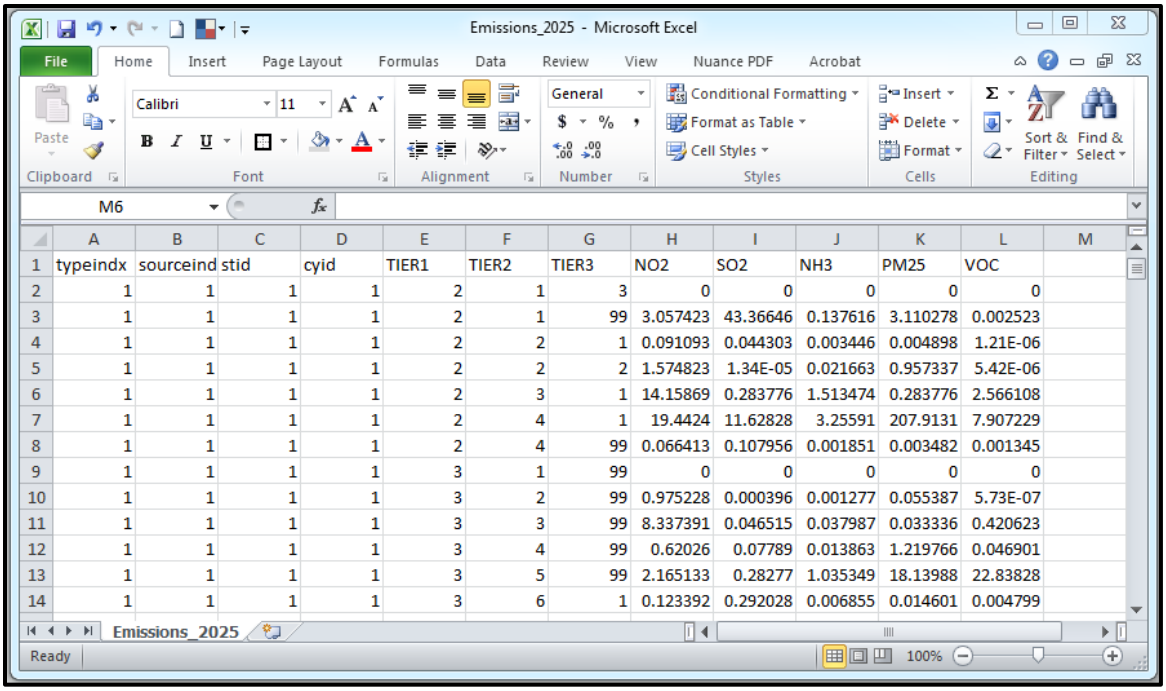
COBRA requires that imported baseline emission files be in a specific format. To create a properly formatted custom baseline emissions file, create a CSV file with the column headings shown in Exhibit 2. Each row of the file should correspond to a different source in a different county.

Exhibit 2. Format of Baseline Emissions File.

Column Heading	Description of Column Headings
typeindx[1]	Stack height associated with the emission
sourceindx[2]	Source index, which COBRA uses in its source receptor model
stid	FIPS state ID (e.g., the state FIPS code for Pennsylvania is 42)
cyid	FIPS county ID (e.g., the county FIPS code for Swarthmore, PA is 045)
TIER1[3]	Emissions category to which emissions source corresponds, at tier 1 level
TIER2[3]	Emissions category to which emissions source corresponds, at tier 2 level
TIER3[3]	Emissions category to which emissions source corresponds, at tier 3 level
NO2	NOx emissions from each source in the baseline
SO2	SO2 emissions from each source in the baseline
NH3	NH3 emissions from each source in the baseline
PM25	Primary PM2.5 emissions from each source in the baseline
VOC	VOC emissions from each source in the baseline

Notes:
[1] A table of typeindx and name is saved on your computer after installing COBRA in the default location, in C:/Program Files/COBRA/input files/data dictionary/typeindx – stack heights.csv.
[2] A table of sourceindx and FIPS is saved on your computer after installing COBRA in the default location, in C:/Program Files/COBRA/input files/data dictionary/SOURCEINDX to FIPS crosswalk.csv.
[3] A table of tier definitions and tier numbers is saved on your computer after installing COBRA in the default location, in C:/Program Files/COBRA/input files/data dictionary/EmissionsTier Definitions.csv.

To see the template for a baseline emissions file, navigate to the folder where you installed COBRA – the default location is C:/Program Files/COBRA/. From there, navigate to input files/emissions/Emissions_2025.csv. This is the default COBRA 2025 emissions baseline, so do not make any changes directly to this file.



typeindx	sourceind	stid	cyid	TIER1	TIER2	TIER3	NO2	SO2	NH3	PM25	VOC
1	1	1	1	2	1	3	0	0	0	0	0
1	1	1	1	2	1	99	3.057423	43.36646	0.137616	3.110278	0.002523
1	1	1	1	2	2	1	0.091093	0.044303	0.003446	0.004898	1.21E-06
1	1	1	1	2	2	2	1.574823	1.34E-05	0.021663	0.957337	5.42E-06
1	1	1	1	2	3	1	14.15869	0.283776	1.513474	0.283776	2.566108
1	1	1	1	2	4	1	19.4424	11.62828	3.25591	207.9131	7.907229
1	1	1	1	2	4	99	0.066413	0.107956	0.001851	0.003482	0.001345
1	1	1	1	3	1	99	0	0	0	0	0
1	1	1	1	3	2	99	0.975228	0.000396	0.001277	0.055387	5.73E-07
1	1	1	1	3	3	99	8.337391	0.046515	0.037987	0.033336	0.420623
1	1	1	1	3	4	99	0.62026	0.07789	0.013863	1.219766	0.046901
1	1	1	1	3	5	99	2.165133	0.28277	1.035349	18.13988	22.83828
1	1	1	1	3	6	1	0.123392	0.292028	0.006855	0.014601	0.004799

To import custom baseline datasets, click on the **Advanced Options** tab at the top of the **1. Select Analysis Year** screen. To import a properly formatted baseline emissions file into COBRA, click **Load a Baseline Emissions CSV File**. In the pop-up window, navigate to the location of your baseline emissions CSV file, click the file, and then click **Open**. If you try to import a baseline emissions file that is incorrectly formatted, COBRA will display an error message that an "unhandled exception has occurred in your application."

To create a properly formatted file with both custom baseline and control scenario emissions, create a CSV file with the headings shown in Exhibit 3. Each row of the file should correspond to a different source in a different county.

Exhibit 3. Format of Baseline and Scenario Emissions File

Column Heading	Description of Column Headings
typeindx[1]	Stack height associated with the emission
sourceindx[2]	Source index, which COBRA uses in its source receptor model
stid	FIPS state ID (e.g., the state FIPS code for Pennsylvania is 42)
cyid	FIPS county ID (e.g., the county FIPS code for Swarthmore, PA is 045)
TIER1[3]	Emissions category to which emissions source corresponds, at tier 1 level
TIER2[3]	Emissions category to which emissions source corresponds, at tier 2 level
TIER3[3]	Emissions category to which emissions source corresponds, at tier 3 level

Column Heading	Description of Column Headings
BASE_NO2	NO_x emissions from each source in the baseline
BASE_SO2	SO_2 emissions from each source in the baseline
BASE_NH3	NH_3 emissions from each source in the baseline
BASE_PM25	Primary $PM_{2.5}$ emissions from each source in the baseline
BASE_VOC	VOC emissions from each source in the baseline
CTRL_NO2	NO_x emissions from each source in the control scenario
CTRL_SO2	SO_2 emissions from each source in the control scenario
CTRL_NH3	NH_3 emissions from each source in the control scenario
CTRL_PM25	Primary $PM_{2.5}$ emissions from each source in the control scenario
CTRL_VOC	VOC emissions from each source in the control scenario
TIER1NAME	Name of emissions category to which emissions source corresponds, at tier 1 level
TIER2NAME	Name of emissions category to which emissions source corresponds, at tier 2 level
TIER3NAME	Name of emissions category to which emissions source corresponds, at tier 3 level
FIPS	FIPS state-county ID (e.g., the state FIPS code for Pennsylvania is 42 and the county FIPS code for Swarthmore, PA is 045, so the state-county FIPS ID is 42045)
STATE	State
COUNTY	County
TYPE	Type denotes the stack height associated with the emission

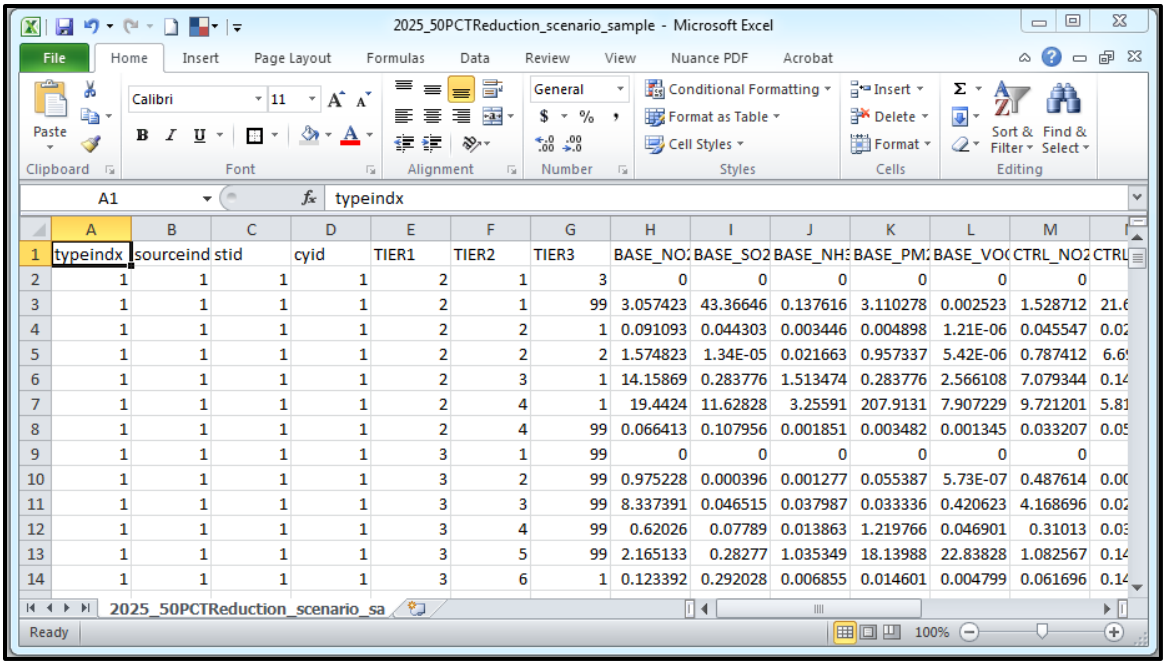
Notes:

[1] A table of typeindx, type, and name is saved on your computer after installing COBRA in the default location, in C:/Program Files/COBRA/input files/data dictionary/typeindx – stack heights.csv.

[2] A table of sourceindx and FIPS is saved on your computer after installing COBRA in the default location, in C:/Program Files/COBRA/input files/data dictionary/SOURCEINDX to FIPS crosswalk.csv

[3] A table of tier definitions and tier numbers is saved on your computer after installing COBRA in the default location, in C:/Program Files/COBRA/input files/data dictionary/EmissionsTier Definitions.csv

To see an example baseline and control scenario emissions file, navigate to the folder where you installed COBRA – the default location is C:/Program Files/COBRA/. From there, navigate to input files/emissionscenarios/ 2025_50PCTReduction_scenario_sample.csv.



typeindx	sourceind	stid	cyid	TIER1	TIER2	TIER3	BASE_NO2	BASE_SO2	BASE_NH3	BASE_PM2	BASE_VO(	CTRL_NO2	CTRL
1	1	1	1	2	1	3	0	0	0	0	0	0	
1	1	1	1	2	1	99	3.057423	43.36646	0.137616	3.110278	0.002523	1.528712	21.6
1	1	1	1	2	2	1	0.091093	0.044303	0.003446	0.004898	1.21E-06	0.045547	0.02
1	1	1	1	2	2	2	1.574823	1.34E-05	0.021663	0.957337	5.42E-06	0.787412	6.6
1	1	1	1	2	3	1	14.15869	0.283776	1.513474	0.283776	2.566108	7.079344	0.14
1	1	1	1	2	4	1	19.4424	11.62828	3.25591	207.9131	7.907229	9.721201	5.81
1	1	1	1	2	4	99	0.066413	0.107956	0.001851	0.003482	0.001345	0.033207	0.05
1	1	1	1	3	1	99	0	0	0	0	0	0	
1	1	1	1	3	2	99	0.975228	0.000396	0.001277	0.055387	5.73E-07	0.487614	0.00
1	1	1	1	3	3	99	8.337391	0.046515	0.037987	0.033336	0.420623	4.168696	0.02
1	1	1	1	3	4	99	0.62026	0.07789	0.013863	1.219766	0.046901	0.31013	0.03
1	1	1	1	3	5	99	2.165133	0.28277	1.035349	18.13988	22.83828	1.082567	0.14
1	1	1	1	3	6	1	0.123392	0.292028	0.006855	0.014601	0.004799	0.061696	0.14

To import a properly formatted baseline and control emissions CSV file into COBRA, click **Load a Baseline Control Scenario Emissions CSV File**. In the pop-up window, navigate to the location of your baseline emissions CSV file, click the file, and then click **Open**.

Custom Population, Incidence, and Valuation Datasets

The **Advanced Options** tab allows users to select customized input files for population data, incidence data, and valuation functions. Note that baseline emissions, population, incidence, and valuation functions vary over time. It is important for input files to correspond to the same year. For example, running COBRA with a 2025 baseline emissions inventory, 2025 population data, and 2025 incidence data would result in COBRA estimating 2025 health benefits. However, running COBRA with a 2025 baseline emissions inventory and 2010 population data would result in theoretical annual health benefits that do not correspond to any calendar year. Alternatively, running COBRA with a projected emissions inventory for 2030 and the default 2025 population and incidence data would assume that population and incidence are constant from 2025 to 2030.

COBRA requires that customized input files be in a specific format. To create a properly formatted population dataset, create a CSV file where each row is a different county and includes the columns listed in Exhibit 4.

Exhibit 4. Format of Population File

Column Heading	Description of Column Headings
Year	Year of population data

Column Heading	Description of Column Headings
DestinationID[1]	DestinationID uses same pattern as SOURCEINDX to indicate destination locations.
FIPS	FIPS state-county ID (e.g., the state FIPS code for Pennsylvania is 42 and the county FIPS code for Swarthmore, PA is 045, so the state-county FIPS ID is 42045)
Age0	Population at age 0
…	Population at each age
Age99	Population older than or equal to 99

[1] See data dictionary file that is saved on your computer after installing COBRA in the default location, in C:/Program Files/COBRA/input files/data dictionary/SOURCEINDX to FIPS crosswalk.csv

To create a properly formatted incidence dataset, create a CSV file where each row is a different county and includes the columns listed in Exhibit 5.

Exhibit 5. Format of Incidence File

Column Heading	Description of Column Headings
Year	Year of population data
DestinationID[1]	DestinationID uses same pattern as SOURCEINDX to indicate destination locations.
FIPS	FIPS state ID (e.g., the state FIPS code for Pennsylvania is 42 and the county FIPS code for Swarthmore, PA is 045, so the state-county FIPS ID is 42045)
Endpoint	Written descriptor indicating health endpoint associated with the recorded incidence rate. (e.g., Acute Bronchitis)
Age0	Incidence of a specific endpoint for population at age 0
…	Incidence of a specific endpoint for population at each age
Age99	Incidence of a specific endpoint for population older than or equal to 99

To create a properly formatted valuation functions dataset, create a CSV file where each row represents a concentration-response function from a single study for a specific age group and includes the columns described in Exhibit 6.

Exhibit 6. Format of Valuation Functions File.

Column Heading	Description of Column Headings
CRFunctionID	ID for C-R functions (linked to the health effect function file)
Endpoint	String descriptor indicating Endpoint for the Valuation function.

Column Heading	Description of Column Headings
PoolingWeight	Functions are pooled accounting to Endpoint. PoolingWeight indicates the relative weight given to this function.
Seasonal_Metric	Daily or Annual are allowable entries. Indicate if computed effect is for a day or an entire year.
Study_Author	Study Author
Study_Year	Study Year
Start_Age	Beginning of age range to which health impact function applies
End_Age	End of age range to which health impact function applies
Function	Functional form that is to be computed. (e.g., (1-(1/((1-Incidence)*Exp(Beta*DELTAQ)+Incidence)))*Incidence*POP)
Beta	Beta parameter supplied to functional form.
Adjusted	Not used
Parameter_1_Beta	Parameter_1_Beta parameter supplied to functional form.
A	A parameter supplied to functional form.
Name_A	Description of A parameter.
B	B parameter supplied to functional form.
Name_B	Description of B parameter.
C	C parameter supplied to functional form.
Name_C	Description of C parameter.
Cases	Not used
HealthEffect	Use same as IncidenceEndpoint
ValuationMethod	Note of valuation method used.
valat3pct	Valuation of health endpoint using 3% discount rate
valat7pct	Valuation of health endpoint using 7% discount rate
IncidenceEndpoint	Indicates Endpoint to use for lookup in Incidence data set.

Custom Health Effect Function Datasets

The **Advanced Options** tab allows users to select customized health effect function datasets. The default health dataset in COBRA relies on an up-to-date assessment of the published scientific literature to ascertain the relationship between particulate matter and adverse human health effects, and can be used for all analysis years. Because of this, most users will not want to modify this input. If you use custom datasets to describe health effect functions, please list the sources of these datasets and any assumptions used to generate them when reporting your results.

If you do choose to import a custom health effect function dataset, COBRA requires that this file be in a specific format. To create a properly formatted health effect functions dataset, create a CSV file where each row represents a concentration-response function from a single study for a specific age group and includes the columns listed in Exhibit 7.

Exhibit 7. Format of Health Effect Functions File.

Column Heading	Description of Column Headings
FunctionID	ID for C-R functions (linked to the valuation function file)
Endpoint	String descriptor indicating endpoint for the Health/Concentration-Response function.
PoolingWeight	Functions are pooled accounting to Endpoint. PoolingWeight indicates the relative weight given to this function.
Seasonal_Metric	Daily or Annual are allowed entries. Indicate if computed effect is for a day or an entire year.
Study_Author	Study Author
Study_Year	Study Year
Start_Age	Beginning of age range to which health impact function applies
End_Age	End of age range to which health impact function applies
Function	Functional form that is to be computed. (e.g., (1-(1/((1-Incidence)*Exp(Beta*DELTAQ)+Incidence)))*Incidence*POP)
Beta	Beta parameter supplied to functional form.
Adjusted	Not used
Parameter_1_Beta	Parameter_1_Beta parameter supplied to functional form.
A	A parameter supplied to functional form.
Name_A	Description of A parameter.
B	B parameter supplied to functional form.
Name_B	Description of B parameter.
C	C parameter supplied to functional form.
Name_C	Description of C parameter.
Cases	Not used
IncidenceEndpoint	Indicates Endpoint to use for lookup in Incidence data set.

Exploring Baseline Emissions Data

You can explore the geographic distribution of pollutant concentrations in the baseline scenario by clicking on the **2. Create Emissions Scenario** tab and then clicking on the **View Emissions Map** tab.

At the top of this screen, you will see a drop-down menu labeled 'Select the field that is to be mapped.' The first five options listed (Base NH3, Base NO2, Base PM2.5, Base SO2, and Base VOC) correspond to the baseline emissions of ammonia (NH_3), nitrogen oxides (NO_x), fine particulate matter ($PM_{2.5}$), sulfur dioxide (SO_2), and Volatile Organic Compounds (VOCs), respectively, from all sectors. Select any of these emissions to view a map of county-level baseline emissions. See Chapter 6 for more details on how to use COBRA's mapping functionality.

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. The scenario definition, results tables, and results maps can be exported for future use or archiving purposes.

The steps to creating a new scenario within the COBRA interface are simple:

Step 1. Select the Analysis Year and Baseline Data. See Chapter 3.

Step 2a. Select the Geography and Tier Level. You can specify emissions changes at the national, state, or county level from fourteen emission source categories.

Step 2b. Enter Emissions Changes. Changes can be made for each state or county, or the entire nation. You can group states and counties and make changes to them together, or make different changes to different geographic areas.

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

To define your scenario, click the **2. Create Emissions Scenario** tab and then the **Emissions Scenario** tab. In the top left panel you can select the geographic area(s) to which you want to apply 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. Click on the appropriate choice in the left panel.

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

- **US.** If you wish to make emissions changes to the entire United States, select 'US.'
- **Individual State.** If you wish to make emissions changes to just one state, click that state.
- **Individual County.** If you wish to make emissions changes to just one county, click that county.

- **Multiple Geographic Areas.** If you wish to make the same emissions changes to multiple geographic areas, click the check box next to each of those geographic areas in the 'Tier and Location Selection' panel. It is possible to select multiple states (e.g., all of California and Oregon), multiple counties (e.g., Dade County, Florida and Broward County, Florida), and combinations of states and counties (e.g., all of Massachusetts and Providence County, Rhode Island).

The 'Pollutants' panel in the top center of your screen will show the total baseline emissions for all the selected geographic areas.

When you apply an emissions change to multiple geographic areas as a percentage, your control scenario will consist of emissions in each county in the selected areas changing by that same percentage. When you apply an emissions change to multiple geographic areas in tons, your control scenario will consist of emissions in each county in the selected areas changing by different amounts that add up to the input total emissions change. COBRA divides the total emissions change across counties in proportion to the baseline emissions. For example, if you input Florida Off-Highway SO_2 emissions decrease by 50 tons, this would correspond to Alachua County Off-Highway SO_2 emissions decreasing by 0.059 tons, Baker County Off-Highway emissions decreasing by 0.003 tons, etc. so that the sum of the SO_2 emission reductions across all Florida counties is 50 tons.

If you have decided to apply different changes to different geographic areas categories, you will need to select the geographic area, select the tier level, and define the scenario emissions separately for each geographic area.

Selecting Tier Level

Next, define the categories of emissions affected. The center panel contains a directory tree with all 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. Click the tier at which you would like to apply your emissions changes. A change entered for a tier category applies to all of the branches under it, but you must enter changes individually for tier categories on separate branches.

Defining Scenario Emissions

After you have selected your tier and geographic area, you can create a new emissions scenario by defining changes to the baseline emissions scenario. This can either be done manually or by uploading an AVERT emissions change data file if you have EPA AVERT model outputs you would like to use.

Manually Entering Emissions Changes

To manually enter the changes to the baseline emissions, use the boxes in the right panel 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. To the right of the boxes you will see the total emissions for your selected tier and geographic area for the baseline and control scenarios. If your emissions scenario attempts to reduce emissions by more than exists in the baseline emissions inventory (e.g., if the SO_2 emissions baseline for Fuel Comb. Elec. Util. in California is 4,065 tons and you try to reduce those emissions by 4,100 tons), you will get the error message "Please make sure you do not try to reduce emissions by more than actually present in the baseline." Click **Apply Changes** to save your changes.

Once your emissions changes are entered for a given tier and location, you can go back and change them by selecting that tier and geographic location again in the directory trees. The emissions baseline and your previously saved control scenario changes will be displayed in the right panel. To overwrite your previously saved control scenario for that tier and location, enter your new emissions changes and click **Apply Changes**.

If you have decided to apply different changes to different geographic areas categories, click the **Clear Selected States or Counties** button and repeat the above steps for each geographic area. For example, if you want to decrease all California Off-Highway SO_2 emissions by 25% and all Oregon Off-Highway SO_2 emissions by 15%, you would have to enter the California emissions change, click **Apply Changes**, click **Clear Selected States or Counties**, enter the Oregon emissions change, and click **Apply Changes** again.

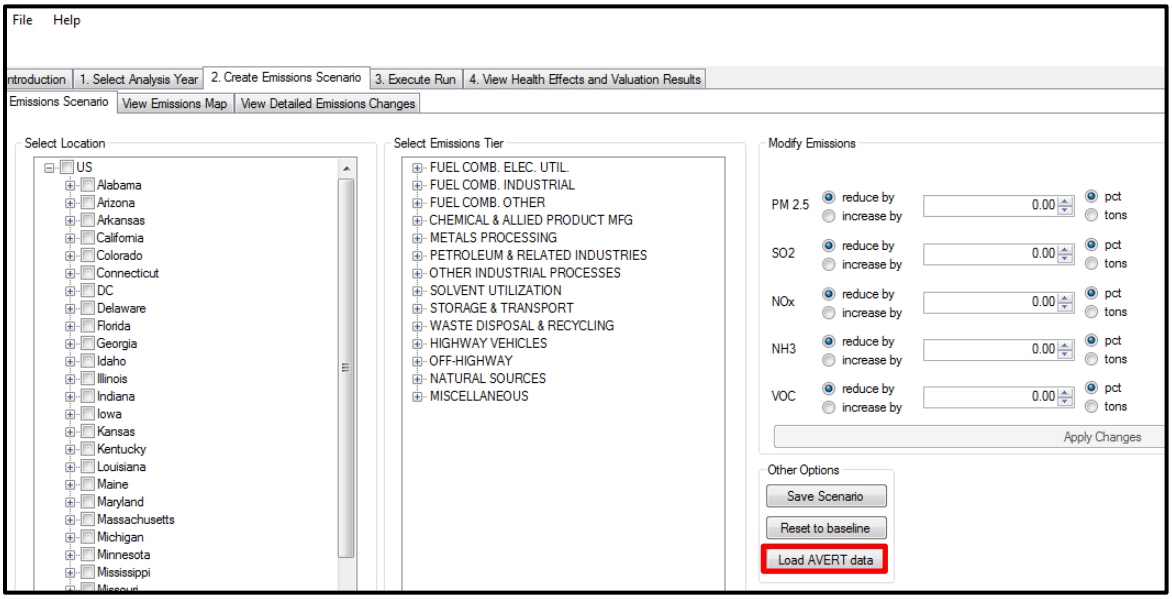
Importing Emissions Changes from AVERT

EPA's AVoided Emissions and geneRation Tool (AVERT) estimates displaced emissions (at the county, state, and regional levels) at electric power plants due to renewable energy or energy efficiency projects, policies, or programs. After running a renewable energy or energy efficiency scenario in AVERT, users can use the AVERT tool to generate a text file for input to COBRA that summarizes the emissions changes that result from that scenario. To access AVERT or to see AVERT output file generation instructions, available in EPA's AVERT user manual, go to https://www.epa.gov/statelocalenergy/avoided-emissions-and-generation-tool-avert.

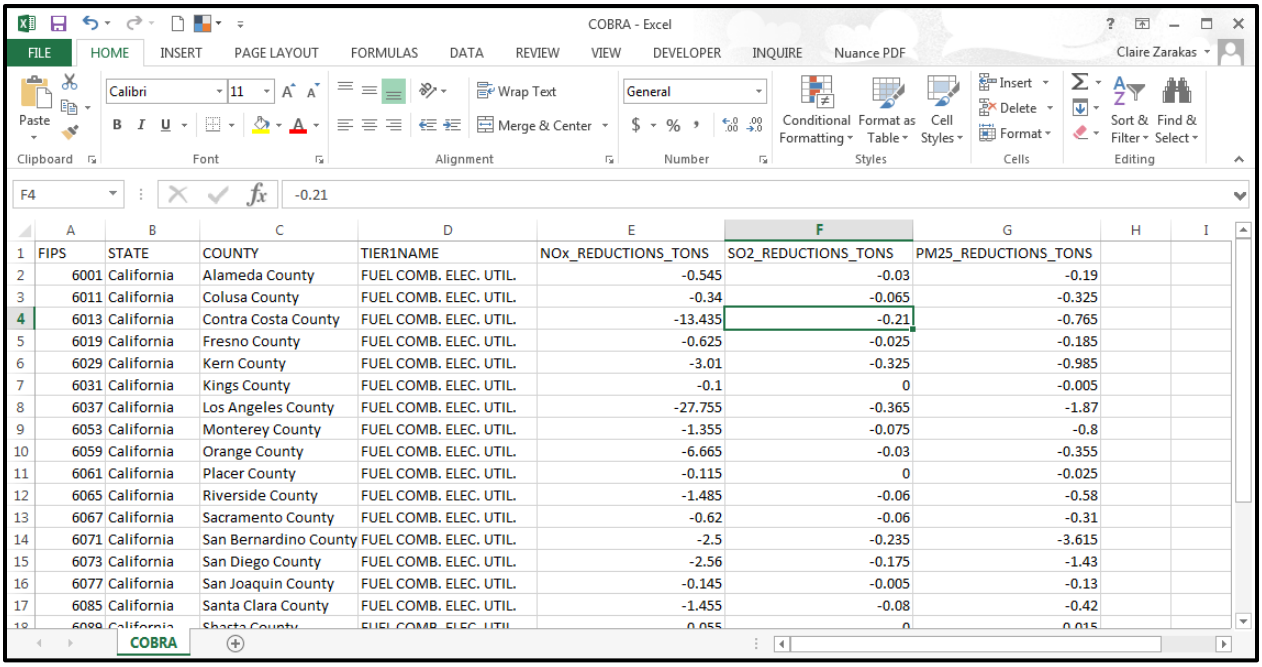
Once the AVERT output file is generated, it can be imported directly into COBRA by clicking the "**Load AVERT output file"** button in the **2. Create Emissions Scenario** tab in COBRA. The emissions reductions from each county from AVERT will be loaded into COBRA in the "Fuel Comb. Elec. Util." tier.

AVERT calculates emissions reductions using 2017 emissions data from EPA; therefore we strongly recommend running COBRA with 2017 as the analysis year for baseline emissions, incidence, population, and valuation inputs. COBRA will display a warning

message if users load an AVERT emissions scenario while using a non-2017 analysis year. If you have entered any emissions changes in the user interface before loading an AVERT emissions scenario file, loading the AVERT file will make COBRA overwrite emissions changes in the Fuel Comb. Elec. Util. tier for the counties included in the AVERT file. Other tiers and counties will be unaffected.



The text file that AVERT generates is already formatted to directly import into COBRA without any modifications. If you choose to edit the AVERT output file, please make sure to maintain the original column headings and file format (example file shown below), such that each row summarizes the emissions reductions in tons for a given county and tier 1 category.



FIPS	STATE	COUNTY	TIER1NAME	NOx_REDUCTIONS_TONS	SO2_REDUCTIONS_TONS	PM25_REDUCTIONS_TONS
6001	California	Alameda County	FUEL COMB. ELEC. UTIL.	-0.545	-0.03	-0.19
6011	California	Colusa County	FUEL COMB. ELEC. UTIL.	-0.34	-0.065	-0.325
6013	California	Contra Costa County	FUEL COMB. ELEC. UTIL.	-13.435	-0.21	-0.765
6019	California	Fresno County	FUEL COMB. ELEC. UTIL.	-0.625	-0.025	-0.185
6029	California	Kern County	FUEL COMB. ELEC. UTIL.	-3.01	-0.325	-0.985
6031	California	Kings County	FUEL COMB. ELEC. UTIL.	-0.1	0	-0.005
6037	California	Los Angeles County	FUEL COMB. ELEC. UTIL.	-27.755	-0.365	-1.87
6053	California	Monterey County	FUEL COMB. ELEC. UTIL.	-1.355	-0.075	-0.8
6059	California	Orange County	FUEL COMB. ELEC. UTIL.	-6.665	-0.03	-0.355
6061	California	Placer County	FUEL COMB. ELEC. UTIL.	-0.115	0	-0.025
6065	California	Riverside County	FUEL COMB. ELEC. UTIL.	-1.485	-0.06	-0.58
6067	California	Sacramento County	FUEL COMB. ELEC. UTIL.	-0.62	-0.06	-0.31
6071	California	San Bernardino County	FUEL COMB. ELEC. UTIL.	-2.5	-0.235	-3.615
6073	California	San Diego County	FUEL COMB. ELEC. UTIL.	-2.56	-0.175	-1.43
6077	California	San Joaquin County	FUEL COMB. ELEC. UTIL.	-0.145	-0.005	-0.13
6085	California	Santa Clara County	FUEL COMB. ELEC. UTIL.	-1.455	-0.08	-0.42

Note that you can paste the results from multiple AVERT runs into a single text file and import it into COBRA. If there are any duplicate counties in the text file, COBRA will sum the emissions reductions before importing the file.

After loading the AVERT emissions scenario, it is possible to manually input additional emissions changes in other counties or tiers. In other words, you can still adjust other tiers besides the "Fuel Comb. Elec. Util." tier, such as the "Highway Vehicles" tier. You can also enter emissions changes in the "Fuel Comb. Elec. Util." tier for counties not included in the AVERT output file. However, if you try to manually adjust the emissions changes in the "Fuel Comb. Elec. Util." tier for a county included in the AVERT output file, this will overwrite the emissions changes from the AVERT output.

> It is also possible to enter a custom scenario definition that is not generated by AVERT into COBRA as a CSV. See the Advanced Options section of Chapter 3 for further instructions on this scenario definition method.

Reviewing Scenario Definition

You can review your scenario definition by looking at the table in the **View Detailed Emissions Changes** tab. This will display all of your changes by state, county, and tier category. If the scenario is acceptable and you wish to save it for future reference, click on the **Emissions Scenario** tab and then click the **Save Scenario** button in the top right panel of the screen. This will export a comma-delimited file that contains the same information as shown in the **View Detailed Emissions Changes** table. Exporting this file

is useful if you export any other tables from the results tabs; at a later date you will have a reference for what the results tables and maps are based on.

Running Scenario

When you have made all of your desired changes, navigate to the **3. Execute Run** tab. This tab asks 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. Therefore, COBRA accounts for the 'time value of money' preference (i.e., a general preference for receiving economic benefits now rather than later) by discounting benefits received later. 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 3 and 7 percent 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.

After selecting a discount rate, click **Run using above options.**

The time to generate your results will vary, depending on the speed of your computer. COBRA may stop responding while it runs, and it may take 5 to 15 minutes to generate results. Once the results are generated, COBRA will navigate to the **4. View Health Effects and Valuation Results** tab, where you can view the results of your run (see Chapter 5).

CHAPTER 5. Viewing Results

Viewing Results in Table Form

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: changes in air quality and health effects between the baseline and control scenarios. You can view results in table form in the **Table** tab or in map form in the **Map** tab.

The **Table** tab describes the changes in air quality (i.e., particulate matter concentration) between the baseline emissions scenario and your scenario (the control scenario), and the corresponding changes in health effects (incidence and monetized values). 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 navigate through the table data in several ways:

- **Scroll** through the data using the scroll bar on the right and bottom of the window.
- **Change the sort order** by clicking on the heading of any column. Click once to sort from smallest to largest and click twice to sort from largest to smallest.
- **Filter column variables** by clicking on the filter button at the top of any column. You can use this functionality to filter down to a specific state and county.
- **Change the column order** by clicking on the column name and dragging it to a new position. When you see a black line, you can drop the column there. Note that the sort order of the table will not change.
- **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 condense or expand the column.
- **View totals** by navigating to the top or bottom of the table. If you filter the table, the totals row will adjust in real time to display the totals for all values that are currently visible. For example, if you have not filtered the table, the totals row will show total health effects for the entire United States. If you have filtered the table to only show results for a specific state, the totals row will show total health effects for that state.

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 table also 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. The table also displays an estimate of the economic value of the change in the number of cases for each health effect. For more information, see Appendix F. Exhibit 8 describes the health endpoints and valuations that are included in the health effects tables in COBRA.

Exhibit 8. Description of Health Effects and their Economic Values

Health Effect	Description
Mortality (low estimate)	Low estimate of the number of deaths, based on Krewski et al. (2009)
$ Mortality (low estimate)	Low estimate of the economic value of the number of deaths, using Krewski et al. (2009) and a discount rate of 3% or 7%
Mortality (high estimate)	High estimate of the number of deaths, based on Lepeule et al. (2012)
$ Mortality (high estimate)	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
Nonfatal Heart Attacks (low estimate)	Low estimate of the number of non-fatal heart attacks, based on four acute myocardial infarction (AMI) studies
$ Nonfatal Heart Attacks (low estimate)	Low estimate of the economic value of non-fatal heart attacks, based on four AMI studies and a discount rate of 3% or 7%
Nonfatal Heart Attacks (high estimate)	High estimate of the number of non-fatal heart attacks, based on Peter et al. (2001)
$ Nonfatal Heart Attacks (high estimate)	High estimate of the economic value of non-fatal heart attacks, using Peter et al. (2001) and a discount rate of 3% or 7%
Hospital Admits, All Respiratory	Number of respiratory-related hospitalizations
Hospital Admits, Asthma	Number of asthma-related hospitalizations
Hospital Admits, Chronic Lung Disease	Number of hospitalizations related to chronic lung disease
$ Hospital Admits, All Respiratory	Economic value of respiratory-related hospitalizations (total across respiratory-related, asthma-related, and chronic lung disease hospitalizations)
Hospital Admits, Cardiovascular (except heart attacks)	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'
$ Hospital Admits, Cardiovascular	Economic value of cardiovascular-related hospitalizations

Health Effect	Description
Acute Bronchitis	Cases of acute bronchitis
$ Acute Bronchitis	Economic value of acute bronchitis cases
Upper Respiratory Symptoms	Episodes of upper respiratory symptoms (runny or stuffy nose; wet cough; and burning, aching, or red eyes)
$ Upper Respiratory Symptoms	Economic value of episodes of upper respiratory symptoms
Lower Respiratory Symptoms	Episodes of lower respiratory symptoms: cough, chest pain, phlegm, or wheeze
$ Lower Respiratory Symptoms	Economic value of episodes of lower respiratory symptoms
Emergency Room Visits, Asthma	Number of asthma-related emergency room visits
$ Emergency Room Visits, Asthma	Economic value of asthma-related emergency room visits
Minor Restricted Activity Days	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).
$ Minor Restricted Activity Days	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

Notes: * For adult mortality and nonfatal 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. 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 and non-fatal heart attacks. 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) used two studies when analyzing proposed NO_2 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 adult deaths avoided and their economic value, respectively, based on Krewski et al. (2009). **Adult Mortality (High)** and **$ Adult Mortality (High)** represent estimates of adult deaths avoided and their economic value, respectively, based on Lepeule et al. (2012). More details on these two studies are available in Appendix C of the user manual.

- **Nonfatal Heart Attacks.** COBRA calculates two estimates of the non-fatal heart attack cases avoided (**Nonfatal Heart Attacks**) and their economic value (**$ Nonfatal 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.

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 over the following 20 years. *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 over the following 20 years 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.

All health effects are monetized. However, to prevent double-counting, the calculation of asthma exacerbations only includes asthma effects occurring in children aged 6 to18 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).

Viewing Results in Maps Form

The **Map** tab displays the results of your scenario geographically. The left 'Select the field that is to be mapped:' drop-down menu 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 **Table** tab), 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 **Table** tab.

Saving Results

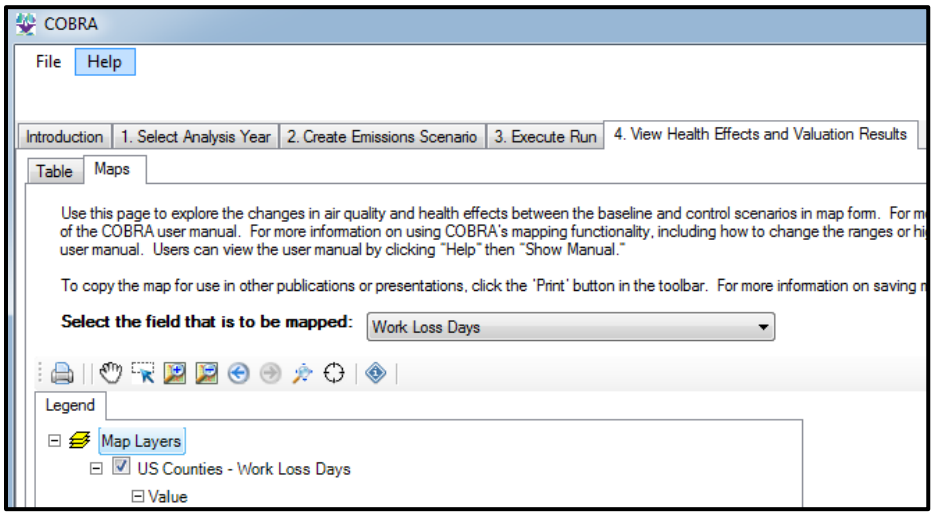
To save your results for use outside of the COBRA environment, you can export the results tables by clicking **Export to CSV** in the **Table** tab. The maps can also be customized within COBRA and then exported for use in documents and presentations (see Chapter 6).

CHAPTER 6. Using Mapping Functionality.

COBRA can create maps of baseline emissions and air quality, control scenario emissions and air quality, changes in air quality, adverse health effects avoided, and the economic value of adverse health effects avoided. To view maps of baseline or control emissions, navigate to the **2. Create Emissions Scenario** tab and click **View Emissions Map** at the top of the page. To view maps of baseline and control air quality, changes in air quality, adverse health effects avoided, and the economic value of adverse health avoided, navigate to the **4. View Health Effects and Valuation Results** tab and click on **Map** tab at the top of the page. Maps of emissions can be viewed before running COBRA, but maps of air quality and health effects can only be viewed after running COBRA.

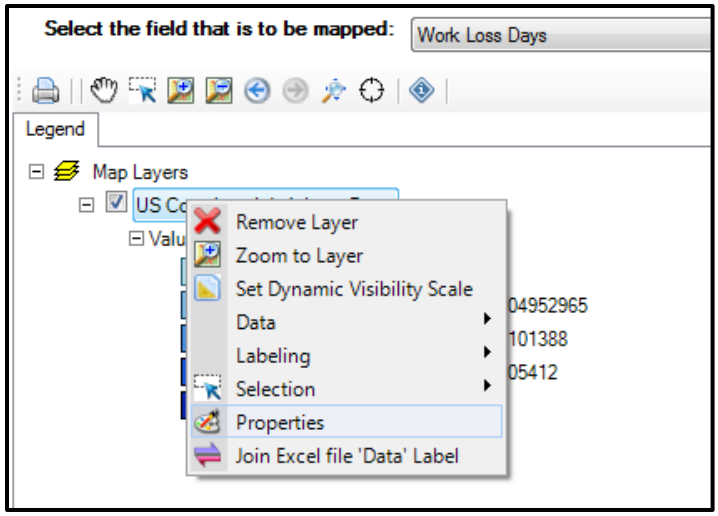
The mapping interface works the same way in both screens. Below, we describe the major capabilities of the mapping tool and show how to use it for the Pennsylvania example described in Chapter 2.

To create a map, select the variable you would like to map in the 'Select the field that is to be mapped' drop-down menu. For this example, you will examine avoided work loss days.

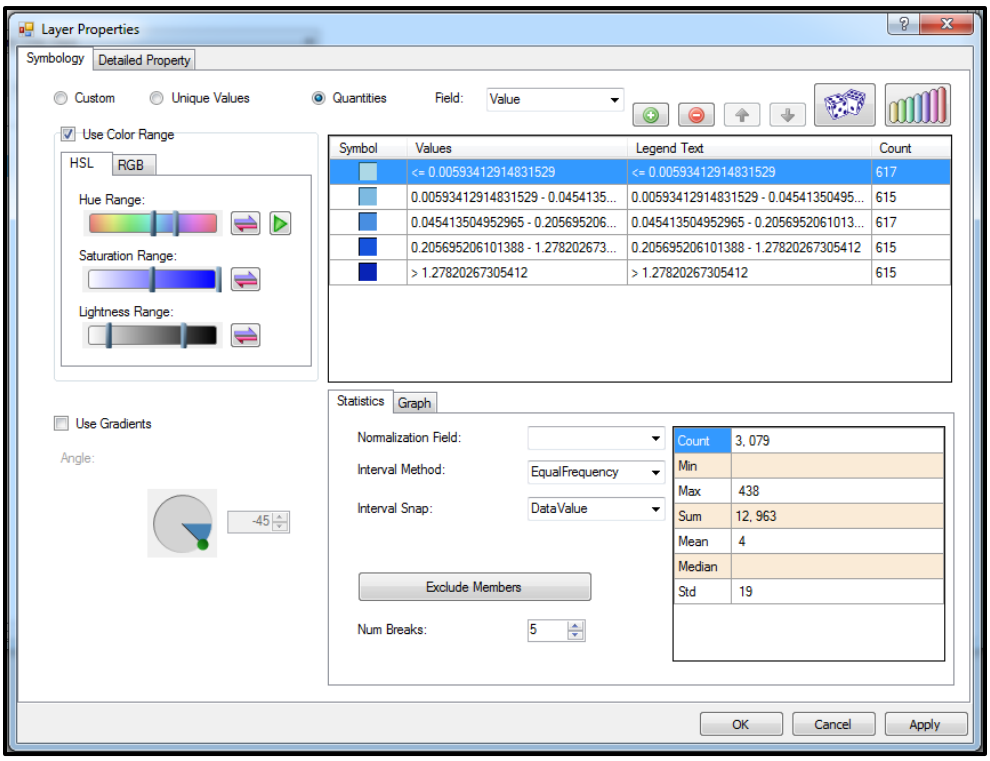


Customizing Map Appearance

To modify the color scheme of the map, right-click 'US Counties' in the Legend panel and then click 'Properties.'

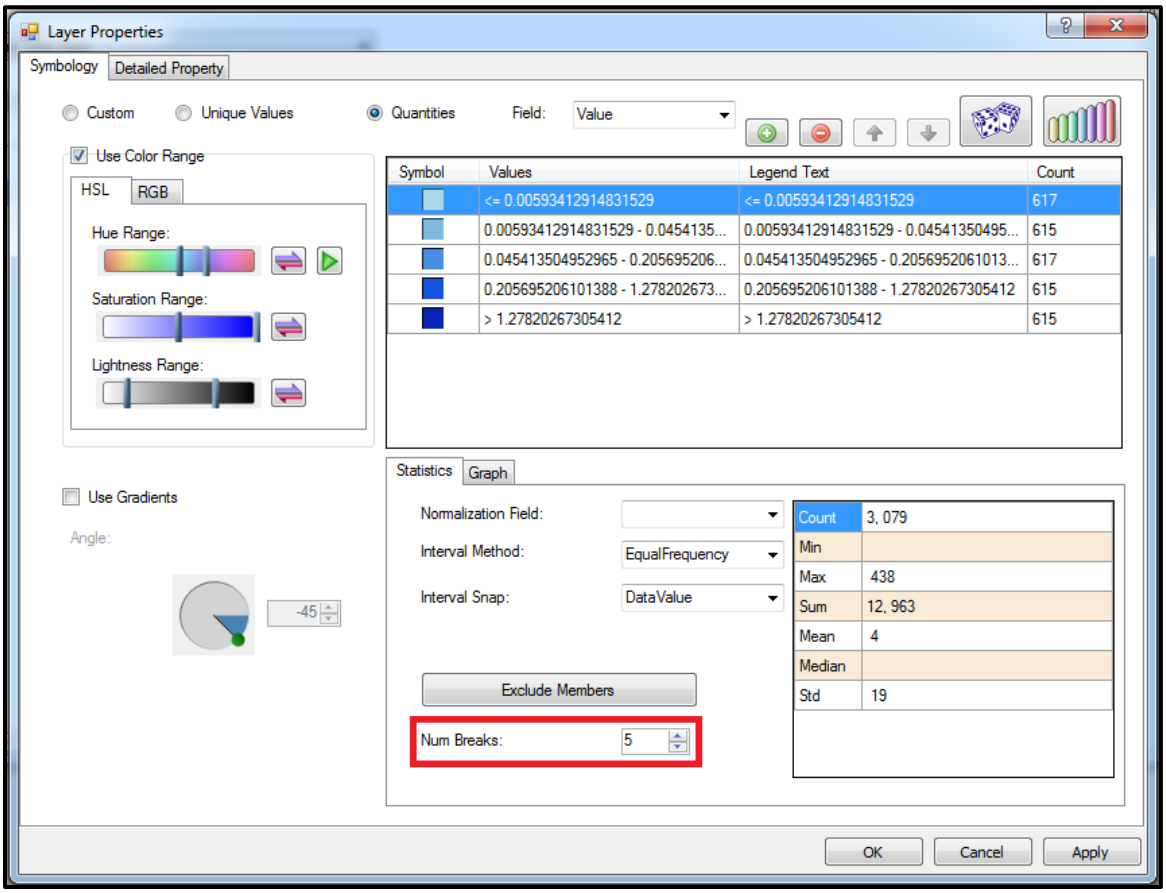


The menu that pops up has three panels. The top left panel allows you to select the overall color scheme that will define the map. The top right panel summarizes the color classification scheme (in this example, the shading that indicates larger numbers of avoided work loss days). The bottom right panel allows you to modify the ranges (or "interval breaks") used in the color classification scheme.



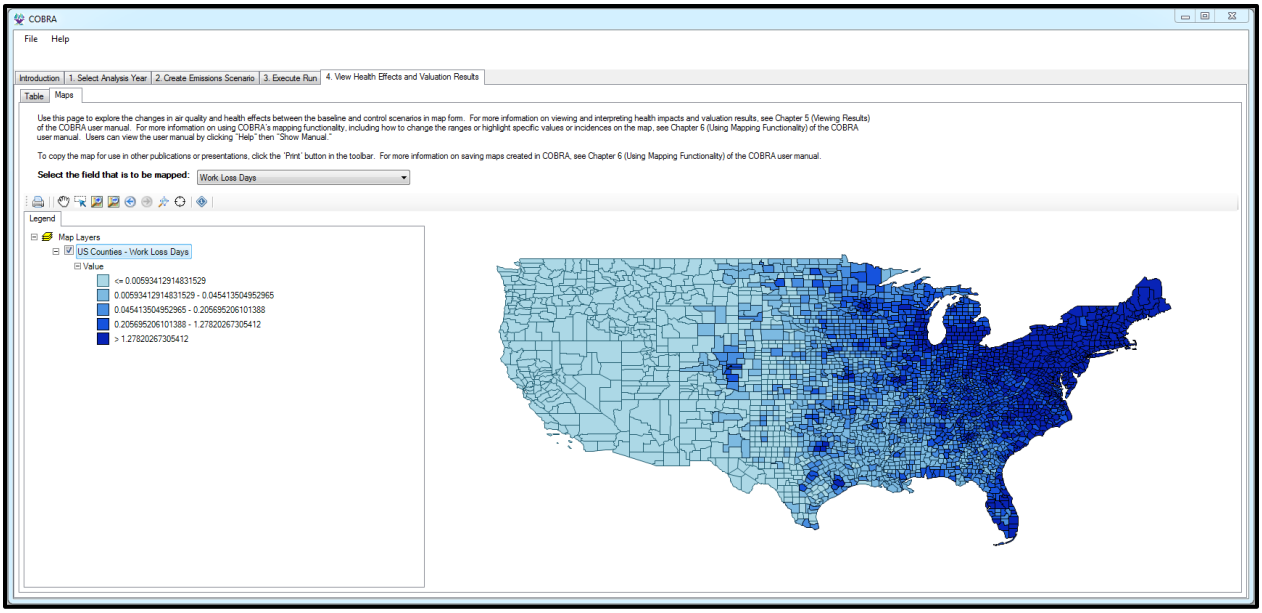
Defining Interval Breaks

You can adjust how color intervals are defined in the bottom right panel. In the box to the right of 'Num Breaks' (indicated in red below), enter the number of intervals you would like your map to have.

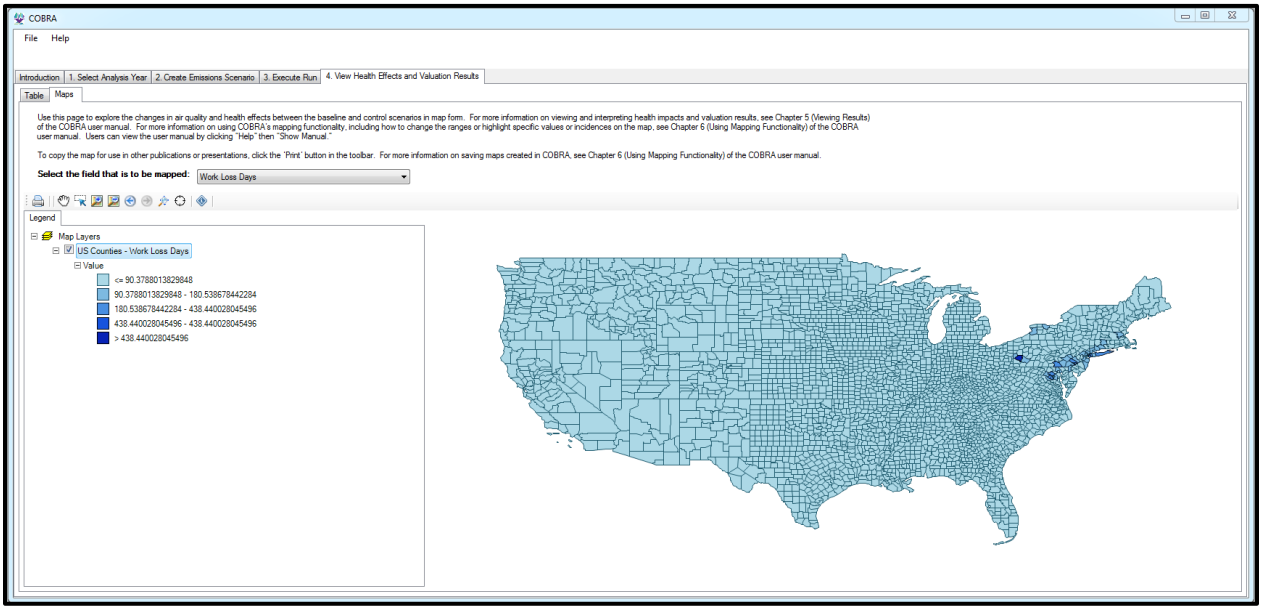


If you select 1, all counties will be in the same interval and the map will be a single color. If you select 10, there will be 10 intervals that can be 10 different colors. In this example, you should select 5. Next, select how COBRA should define the intervals. There are four possible methods, described below.

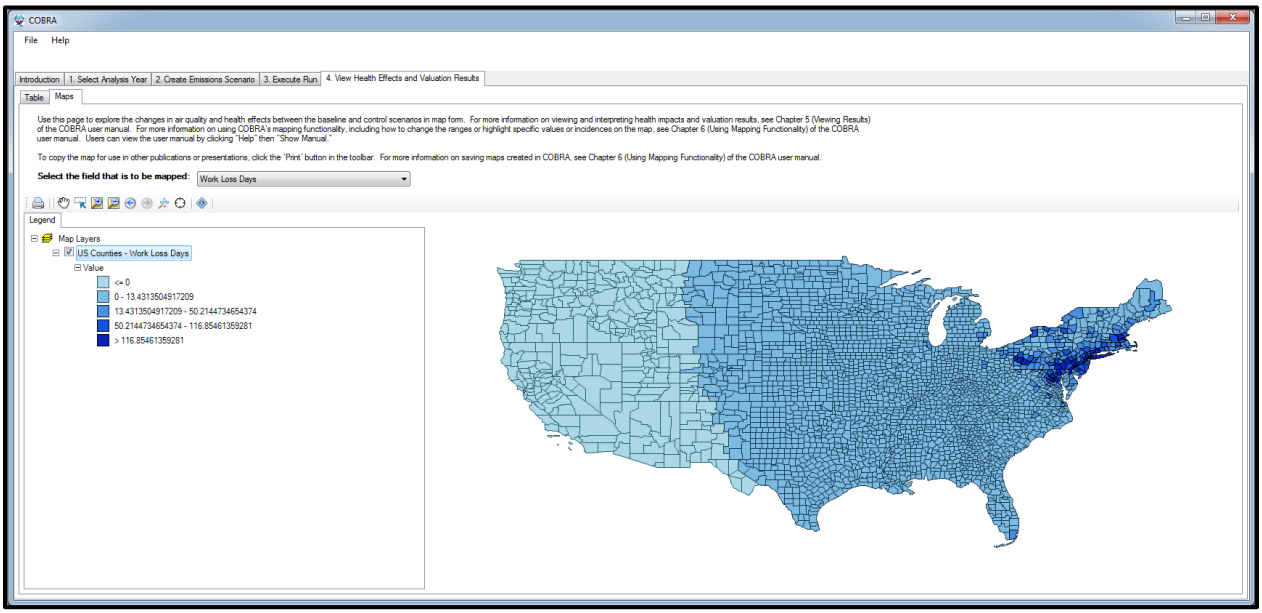
- **Equal Frequency.** This method takes the range of the values, and, using the number of breaks you selected, splits the range into intervals where each interval contains the same number of counties. Below is the map of avoided work loss days where intervals are defined using the equal frequency option. This is COBRA's default setting.



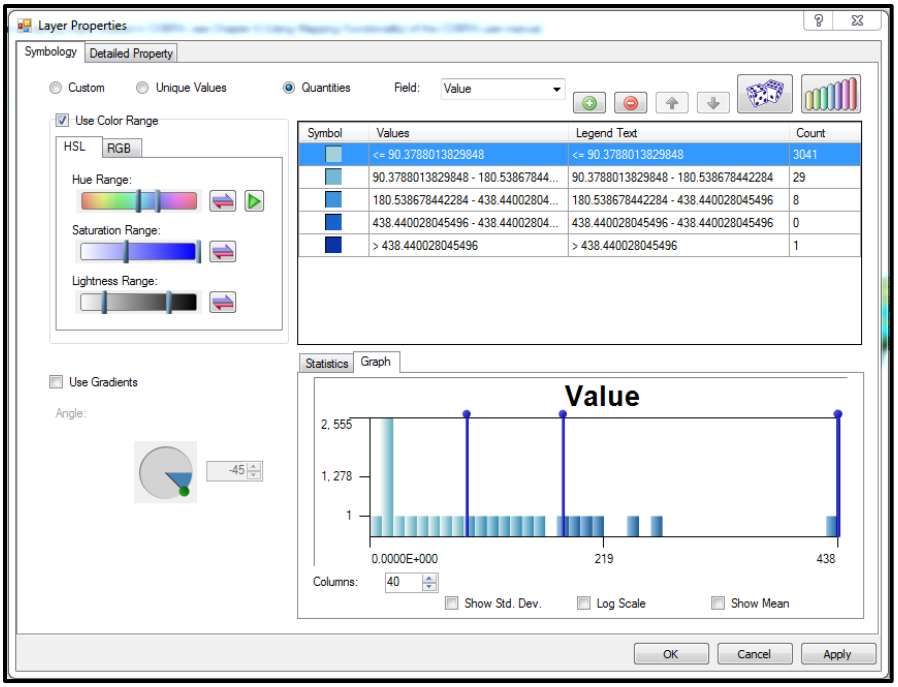
- **Equal Intervals.** This method takes the range of the values for all counties in the U.S., and, using the number of breaks you selected, splits the range into equal intervals. Below is the map of avoided work loss days where intervals are defined using the equal intervals option.



- **Natural Breaks.** This method divides counties into groups where the values (e.g., for avoided work loss days) are similar within groups and less similar to counties in other groups (based on variance in the values). Below is the map of avoided work loss days where intervals are defined using the natural breaks option.



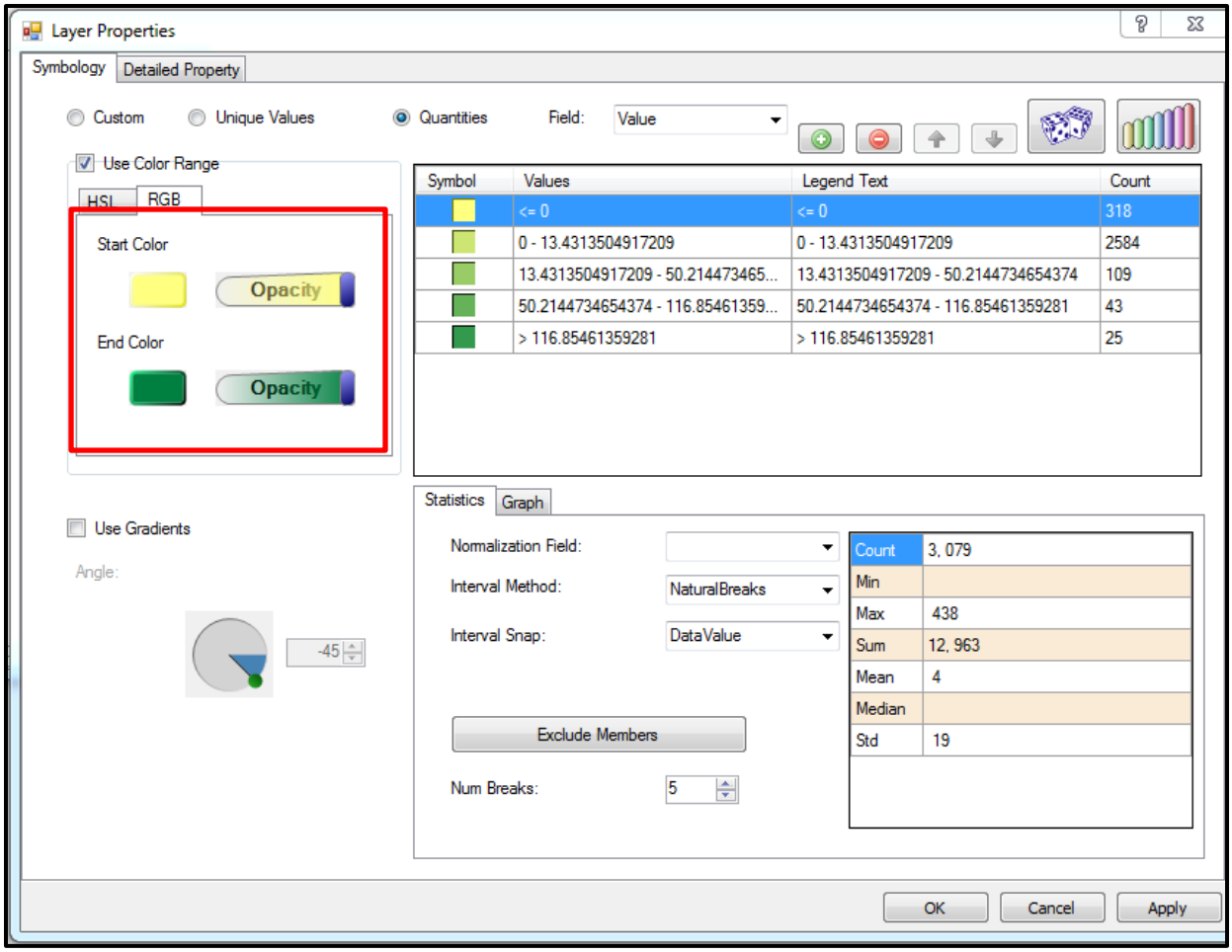
Manual. This method allows you to manually enter the range of each interval. To do so, click the **Graph** tab in the bottom right panel. This displays the distribution of values across all counties in the United States in a histogram. The x-axis is the value you are mapping (in this example, work loss days avoided) and the y-axis is the number of counties. The height of each rectangle is the number of counties with avoided work loss days within the range defined by the base of that rectangle. The blue lines are the boundaries defining the intervals for your color scheme. To change these boundaries, click on one of the blue lines and drag it to the boundary you want.



The method used to define a map's interval boundaries affects the conclusions that are likely to be drawn from the map, so it is important that users exercise care in selecting interval definition schemes. In this example, you can choose to define intervals using the Natural Breaks method.

Changing Color Scheme

Navigate to the top left panel to change the map's color scheme. To create a simple spectrum that fades from one color to another color, click the **RGB** tab. Click the 'Start Color' box and select a color to represent the boxes with the smallest value. Then, click the 'End Color' box and select another color to represent the color with the largest value. In this example, choose yellow to represent counties with the smallest number of avoided work loss days and green to represent counties with the largest number of work loss days avoided.



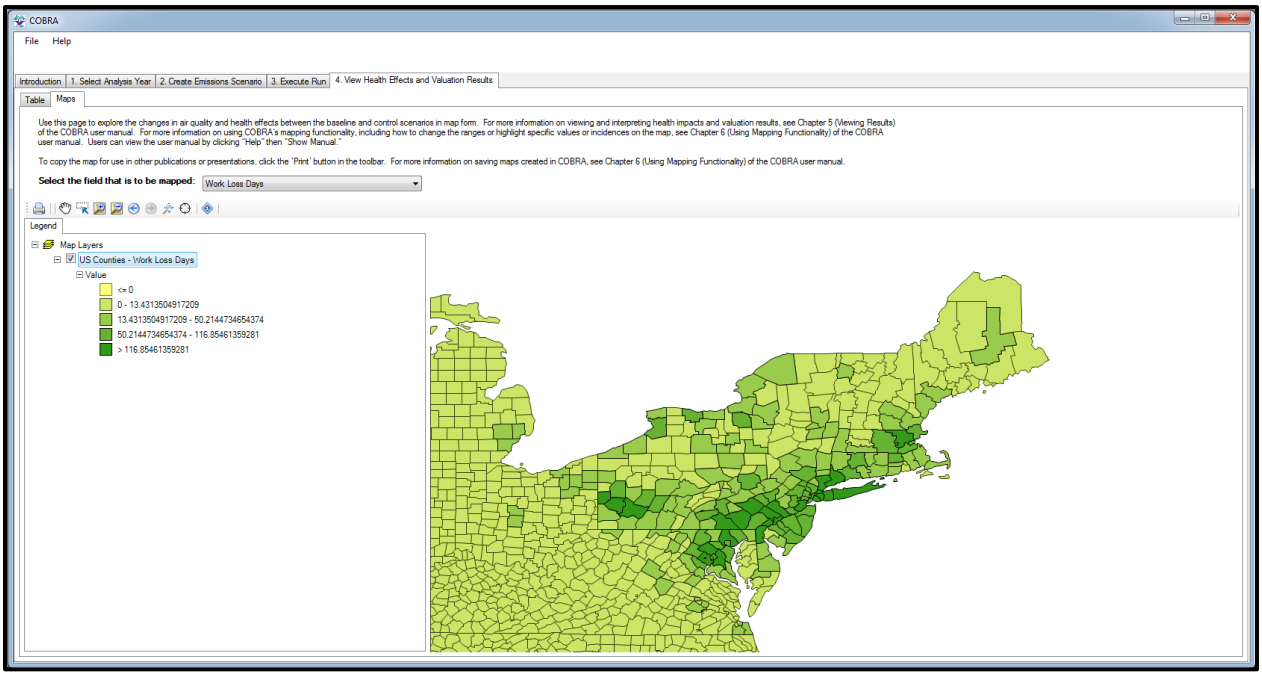
After selecting interval breaks and deciding on a color scheme, you can review your selections in the top right panel. The 'Symbol' column shows the color that will represent all counties within each interval. The 'Values' column summarizes the definition of each interval. The 'Count' column lists the number of counties within each interval. The 'Legend Text' column displays the text that will be displayed in the legend. You can modify the legend text by double-clicking on the text.

After creating the desired color scheme, click **Apply**.

Modifying Map Scale

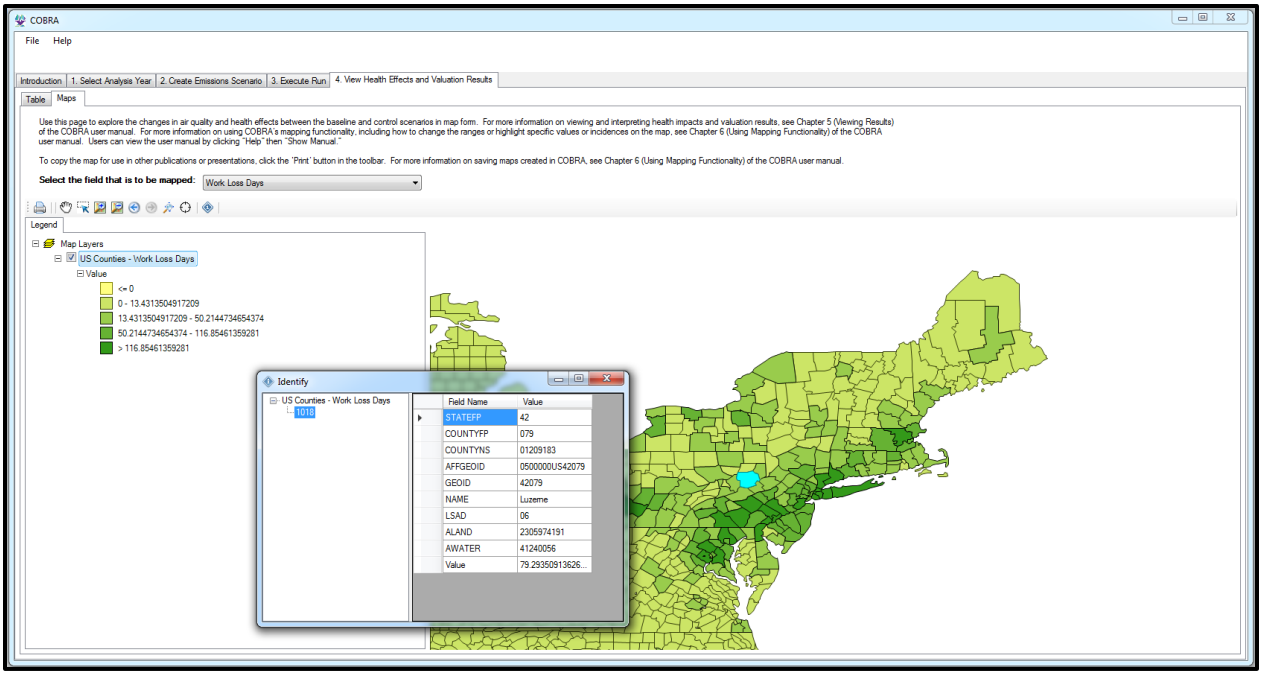
You can zoom in or out on the map by selecting **Zoom In** ( ) or **Zoom Out**( ) in the top left toolbar and then clicking anywhere on the map. You can also zoom in on a specific area by clicking the **Zoom In** tool and then drawing a box with left mouse button depressed. To pan, click the **Pan** button ( ) and then click and drag the map to the portion you wish to view. You can toggle between extents (i.e. map scales) by clicking **Zoom to Previous Extent** ( ) and **Zoom to Next Extent** ( ). To zoom out to the full U.S., click **Zoom to Maximum Extents** ( ). To center the map at a specific location, click **Zoom to Coordinates** ( ) and input the

relevant latitude and longitude coordinates. Because this scenario focused on emissions reductions in Pennsylvania, in this example you will zoom in to the Northeast United States.

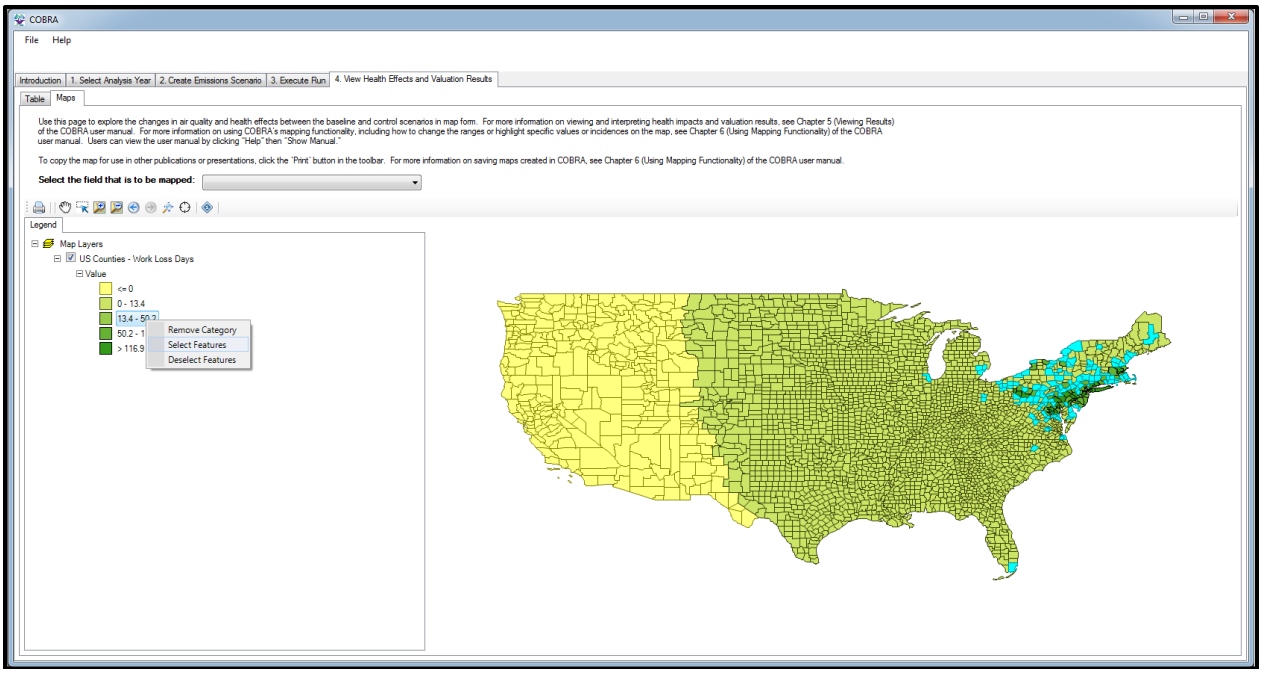


Exploring Data

To get map information about a specific county, click the **Identifier** button ( ) in the top left toolbar and then click the county of interest. The selected county will be highlighted in teal and a box will pop up that contains the name of the county, the estimate for the value you are mapping for this county (e.g., avoided work loss days), and other identifying information for the county. For example, if you select Berks county, Pennsylvania you will see that the emissions reduction scenario will avoid about 134 work loss days in this county.



To select all counties that have values in a given interval (as described in the "Defining Interval Breaks" section above), right click on the interval in the Legend and then click 'Select Features.'



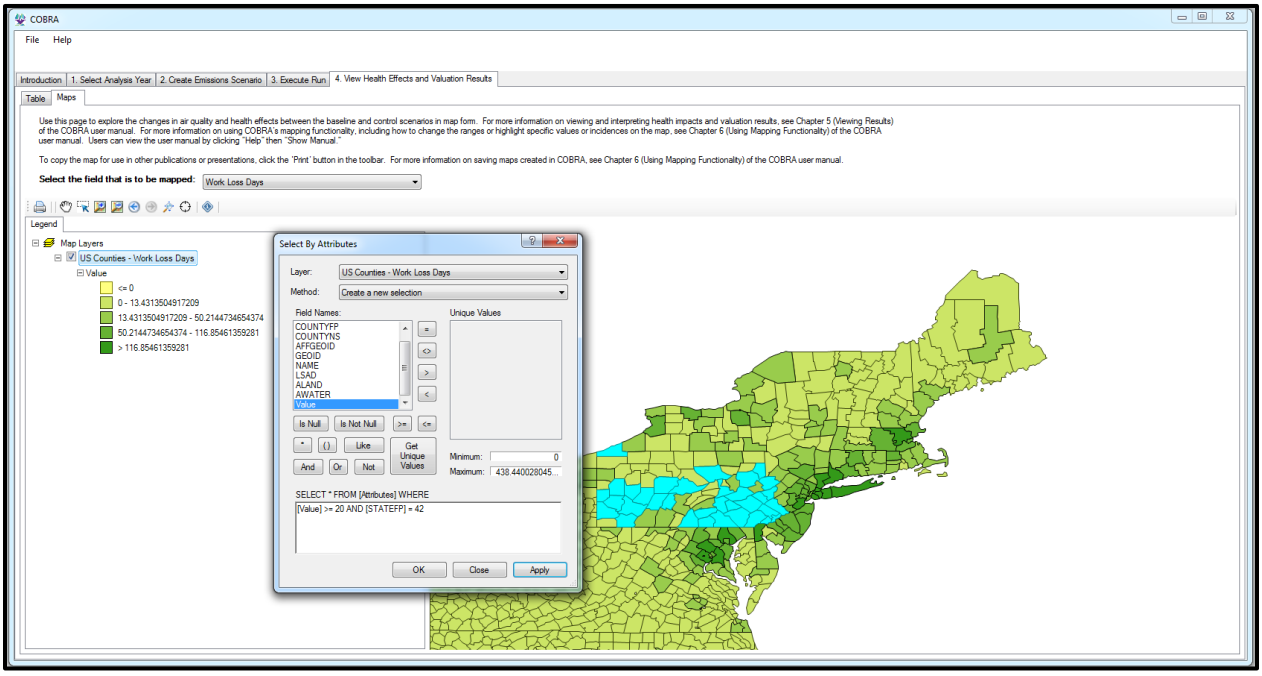
To find counties that match some criterion, right click the 'US Counties' drop-down, then click **Selection…Select by Attributes**. You can fill the box with the criteria you are interested in. For example, if you want to see which counties have more than 20 avoided work loss days and are

also located in Pennsylvania (which has a state FIPS code of 42[9]), you can make selections from the 'Field Names' list in the upper left of the pop up box. For this example, you would:

- First, double-click Value from the 'Field Names' list, click the '>=' button, and then type 20. This sets the criterion for at least 20 avoided work loss days.
- You would then add the criterion for counties located in Pennsylvania as follows: click the 'And' button, double-click STATEFP from the 'Field Names' list, click the '=' button, and then type 42.

Alternatively, once you are familiar with this functionality, you could simply write this equation in the box at the bottom of the window: "[Value]>=20 AND [STATEFP]=42".

Once you have described your selection, click **Apply**. COBRA will highlight the counties that fit your criteria in teal.



Exporting Map

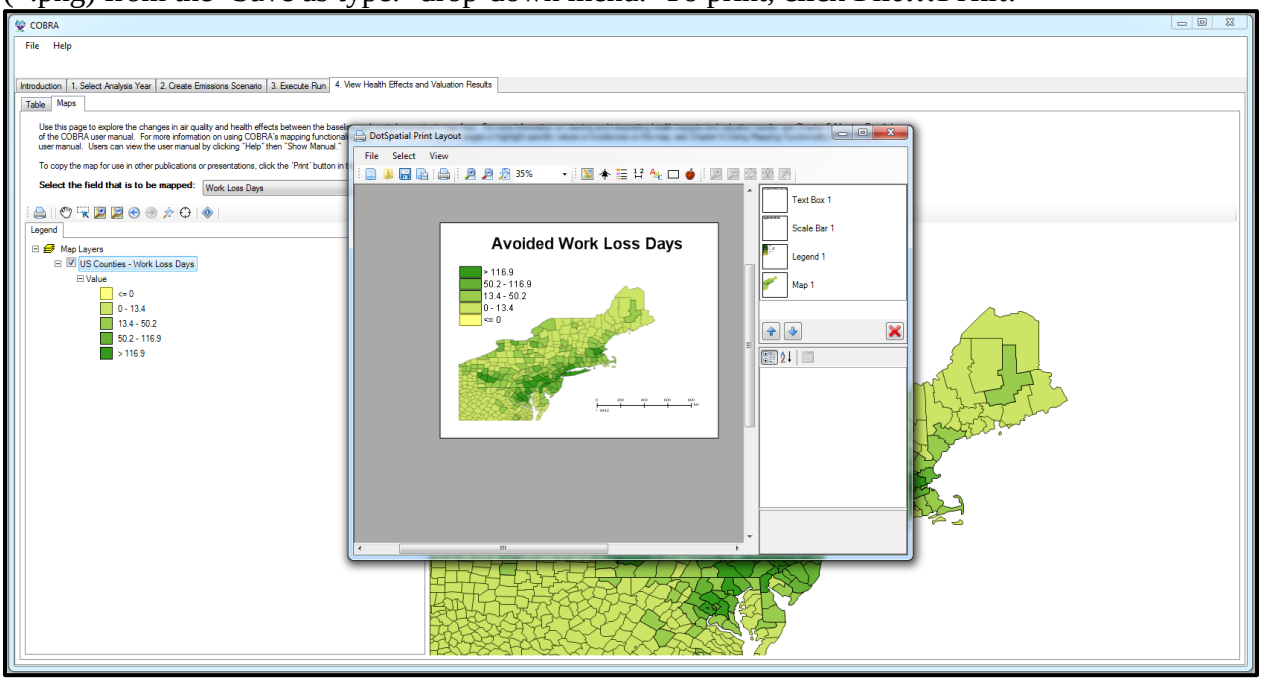
Printing or Exporting Map as Image

To print the map or export a map as an image, click the **Print** button (🖶) in the toolbar. To modify how much space the map takes up on the page, click the map, then click the bottom right

[9] FIPS codes uniquely identify United States counties and states. Codes can be accessed at: https://www.census.gov/geo/reference/codes/cou.html.

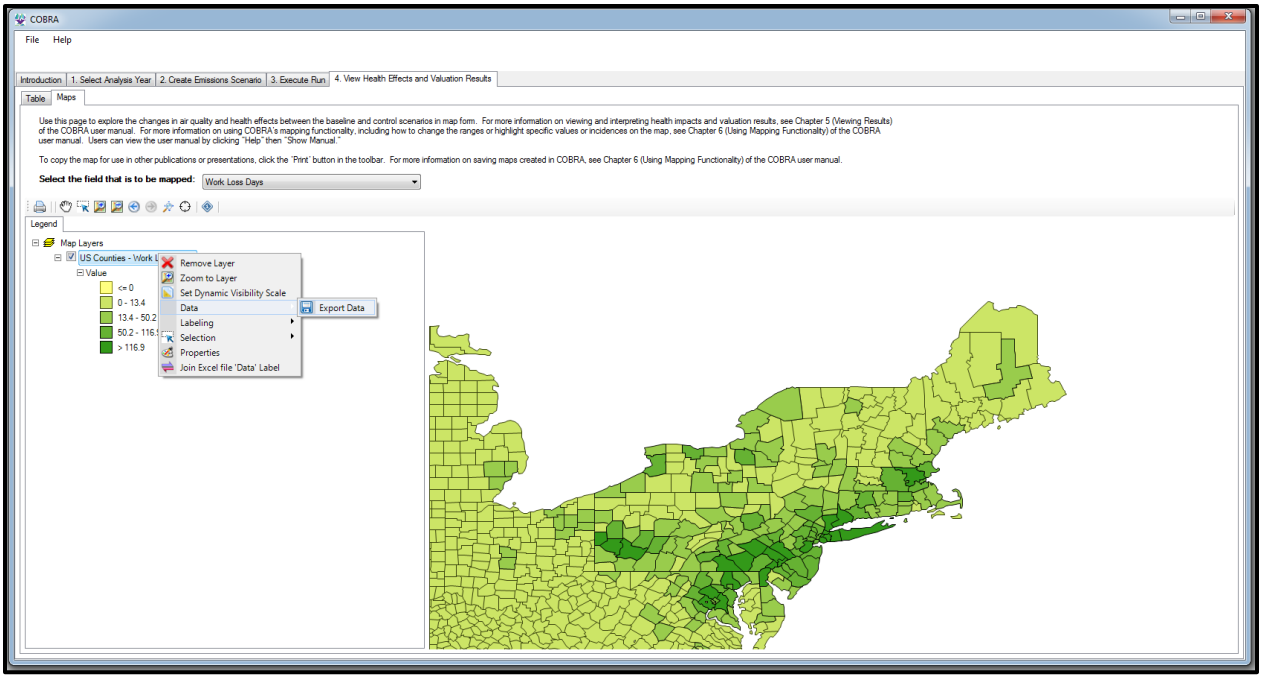
corner of the map and drag the rectangle. You can also click the center of the map and move it elsewhere on the page. You can zoom in and out and pan using the tools in the right hand side of the screen. To change the orientation of the page, click **File…Page Setup** then click Landscape. You can also add a compass, legend, scale bar, or text box from the toolbar. To edit the text box, click the text box and then edit the "Text" row in the bottom right panel. For example, you can add a title to the map "Avoided Work Loss Days" in a text box.

To save the map as an image, click **File…Save As** and then click Portable Network Graphics (*.png) from the 'Save as type:' drop-down menu. To print, click **File…Print**.



Exporting Map for Use in Other Mapping Software

To export the map as a shapefile, right click 'US Counties' in the Legend tab. Then click **Data**…**Export Data**. Click the folder icon to navigate to the folder where you would like to save the map, and select 'DotSpatial.Shapefile – Shapefiles (*.shp)' from the 'Save as type:' drop-down menu. Click **Save**.


COBRA
File
Help
Introduction
1. Select Analysis Year
2. Create Emissions Scenario
3. Execute Run
4. View Health Effects and Valuation Results
Table
Maps
Use this page to explore the changes in air quality and health effects between the baseline and control scenarios in map form. For more information on viewing and interpreting health impacts and valuation results, see Chapter 5 (Viewing Results) of the COBRA user manual. For more information on using COBRA's mapping functionality, including how to change the ranges or highlight specific values or incidences on the map, see Chapter 6 (Using Mapping Functionality) of the COBRA user manual. Users can view the user manual by clicking "Help" then "Show Manual."
To copy the map for use in other publications or presentations, click the "Print" button in the toolbar. For more information on saving maps created in COBRA, see Chapter 6 (Using Mapping Functionality) of the COBRA user manual.
Select the field that is to be mapped:
Work Loss Days
Legend
Map Layers
US Counties - Work L
Value
<= 0
0 - 13.4
13.4 - 50.2
50.2 - 116.9
> 116.9
Remove Layer
Zoom to Layer
Set Dynamic Visibility Scale
Data
Export Data
Labeling
Selection
Properties
Join Excel file 'Data' Label

Glossary

Baseline emissions scenario: The emissions estimates for a given year in absence of a policy, ambient pollution levels and health impacts for that year. The baseline emissions 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.

Cross-State Air Pollution Rule (CSAPR): An EPA regulation issued in September 2016 to reduce summertime power plant NOx emissions in 22 states in the eastern United States. For more information on the rule, see https://www.epa.gov/airmarkets/final-cross-state-air-pollution-rule-update.

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

Federal Information Processing Standards (FIPS) geographic codes: codes which uniquely identify United States counties and states. Codes can be accessed at https://www.census.gov/geo/reference/codes/cou.html.

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 https://www.epa.gov/mats

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.

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:

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

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:

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

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.[10] These assumptions are necessary since the spatial variation of emissions within a county cannot be provided for a national scale model.[11]

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

[10] 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*).

[11] 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.

of the source area are assumed to receive the same concentration of pollutants as the source area. 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:

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

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):

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

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):

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

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 SO_2 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 EPA's 2011 Version 6.2 Air Emissions Modeling Platform (2011v6.2 platform) to forecast ambient 2017 and 2025 $PM_{2.5}$ levels in COBRA.[12] The emissions modeling platform has been used by EPA for the Final 2015 National Ambient Air Quality Standards (NAAQS) for Ozone, the 2011 National Air Toxics Assessment (NATA), and the Proposed Cross-State Air Pollution Update Rule (CSAPR). The 2017 and 2025 emissions inventories contain predicted emissions that reflect federal and state measures (promulgated or under reconsideration) as of December 2014. The assumptions underlying the emission inventories are detailed in the Technical Support Document for the Preparation of Emissions Inventories for the Version 6.2, 2011 Emissions Modeling Platform (U.S. EPA, 2015). The 2017 and 2025 base cases include:

- electrical generating unit emissions (reflecting the implementation of both the Mercury and Air Toxics Standards Rule and CSAPR),[13]
- mobile emissions (reflecting changes in activity data and the impacts of the Light Duty Vehicle Greenhouse Gas Rule for Model-Year 2017-2025, the Tier 3 Motor Vehicle Emission and Fuel Standards Rule, and local inspection and maintenance programs), and
- base year-specific fire data for 2011.

In addition to the 2017 and 2025 base case emission inventories, we used a 2011 base case emissions inventory to help develop calibration factors (discussed in more detail in a later section). Exhibit A-2a, Exhibit A-2b, and Exhibit A-2c summarize the 2011, 2017, and 2025 emissions data for the continental U.S. that we used.

[12] Note that 2011 county-level natural emissions (from plants and soil) were estimated using the county total annual emissions by sector (available for download at ftp://ftp.epa.gov/EmisInventory/2011v6/v2platform/reports/) for EPA's 2011 Version 6.2 Air Emissions Modeling Platform.

[13] The 2025 base case does not reflect the Clean Power Plan.

Exhibit A-2a. 2011 Emissions Inventory Summary, by Tier 1 (tons/year)

Tier 1	NO_2	SO_2	$PM_{2.5}$	VOC	NH_3
Fuel Combustion Electric Utilities	1,940,336	4,550,202	195,422	38,626	24,241
Fuel Combustion Industrial	1,168,769	658,030	217,257	108,794	12,519
Fuel Combustion Other	585,250	225,557	416,976	475,281	65,435
Chemical & Allied Product Manuf.	51,268	126,230	17,007	83,000	23,087
Metals Processing	70,503	144,409	48,298	34,183	1,124
Petroleum & Related Industries	677,231	117,975	28,978	2,641,624	1,376
Other Industrial Processes	350,812	188,074	272,505	327,853	33,588
Solvent Utilization	1,090	141	3,868	2,768,209	617
Storage & Transport	19,546	9,276	20,584	1,026,393	6,003
Waste Disposal & Recycling	83,022	16,747	164,176	130,491	35,680
Highway Vehicles	5,719,979	29,665	194,690	2,709,470	120,805
Off-Highway Vehicles	2,949,483	115,688	204,256	2,107,501	3,206
Natural Sources	1,020,456			40,400,933	
Miscellaneous	450,238	184,643	4,373,454	4,770,908	3,854,871
Total	**15,087,984**	**6,366,636**	**6,157,472**	**57,623,265**	**4,182,553**

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

Tier 1	NO_2	SO_2	NH_3	$PM_{2.5}$	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**

Exhibit A-2c. 2025 Emissions Inventory Summary, by Tier 1 (tons/year)

Tier 1	NO_2	SO_2	NH_3	$PM_{2.5}$	VOC
Fuel Combustion Electric Utilities	1,478,966	1,496,592	214,508	47,447	49,598
Fuel Combustion Industrial	1,062,280	343,147	241,020	135,765	10,556
Fuel Combustion Other	553,412	82,955	388,626	439,491	63,354
Chemical & Allied Product Manuf.	47,609	102,864	17,757	95,688	22,776
Metals Processing	64,488	102,004	47,745	34,568	1,142
Petroleum & Related Industries	744,384	131,340	35,092	3,563,768	1,314
Other Industrial Processes	360,765	177,002	278,998	330,202	33,792
Solvent Utilization	1,152	143	3,855	2,818,279	627
Storage & Transport	19,100	6,427	20,486	731,861	6,013
Waste Disposal & Recycling	61,245	14,368	165,097	131,896	35,541
Highway Vehicles	1,707,692	13,759	83,019	904,713	85,521
Off-Highway Vehicles	1,730,482	25,179	95,871	1,248,662	4,125
Natural Sources	1,020,456			40,400,933	
Miscellaneous	435,873	184,109	4,654,847	4,769,534	3,949,954
Total	**9,287,904**	**2,679,889**	**6,246,922**	**55,652,806**	**4,264,313**

We estimate the formation of SOA using a fixed relationship between SOA and VOC for each Tier 3 emission category.[14] EPA's 2011v6.2 platform 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 emissions inventory from the 2011v6.2 platform:

$$\mathrm{SOA}_{\mathrm{2011v6.2,\ Tier\ 3}} = \mathrm{VOC}_{\mathrm{2011v6.2,\ Tier\ 3}} \cdot \left(\frac{\mathrm{SOA}_{\mathrm{CSA,\ Tier\ 3}}}{\mathrm{VOC}_{\mathrm{CSA,\ Tier\ 3}}}\right)$$

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 determinants[15] of how far emissions

[14] 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.
[15] The other determinants include wind speed and direction as well as atmospheric chemistry.

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.[16] 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.[17]

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.

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 tapes[18] 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

[16] In a very small number of cases (0.32% of records in the emissions baseline), there are point source emissions in multiple stack height groups for the same Tier 3 emission category in the same county. When emissions changes are entered in the COBRA model for these cases, the changes are apportioned to stack height groups in proportion to the baseline scenario emissions.

[17] 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.

[18] 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.

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 (SO_2), (3) nitrogen dioxide (NO_2), and (4) ammonia (NH_3). 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/m^3) 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/m^3 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.

The pollutant concentration at a destination county is given by:

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

where:

D_j^s = Concentration of pollutant s at destination county j (μg/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 μg-year/ton-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

Species	Symbol	Standard molecular weight [19]
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	$(NH_4)_2SO_4$	132.13952

Exhibit A-5. Ionic Conversion Factors

Species	Ionic conversion factor, F^s
PM_{25}, SOA	1
$SO_2 \rightarrow SO_4^{2-}$	96.0626 / 64.0638
$NO_2 \rightarrow NO_3^-$	62.0049 / 46.0055
$NH_3 \rightarrow NH_4^+$	18.03846 / 17.03052

Atmospheric Chemistry

This section describes how secondary reactions are modeled in COBRA, including formation of ammonium bisulfate (NH_4HSO_4), ammonium sulfate ($(NH_4)_2SO_4$), and ammonium nitrate (NH_4NO_3). 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 models[20] (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 (SO_4^{2-}) and nitrate (NO_3^-), ammonium (NH_4^+) reacts preferentially with SO_4^{2-} to form NH_4HSO_4 and $(NH_4)_2SO_4$. NH_4NO_3 is only formed under conditions of excess NH_4^+ and low temperatures. In each destination county, the relative amounts of each secondary particle are subject to the following assumptions:

- SO_4^{2-} is always assumed to be a particle;
- NO_3^- is assumed to be a gas, unless is combines with NH_4^+;

[19] Standard atomic weights from Coursey, et al. (2011).
[20] See U.S. EPA (2012).

- NH_4^+ reacts first with SO_4^{2-}. The nature of the reaction depends on the relative amounts of NH_4^+ and SO_4^{2-}:
    - If there is a little NH_4^+, then SO_4^{2-} will be converted to NH_4HSO_4 with potentially some leftover SO_4^{2-};
    - If there is an intermediate amount of NH_4^+, then a combination of NH_4HSO_4 and $(NH_4)_2SO_4$ will be obtained;
    - If there is a lot of NH_4^+, then SO_4^{2-} will be completely converted to $(NH_4)_2SO_4$;
- After all reactions between NH_4^+ and SO_4^{2-} occur, any remaining NH_4^+ reacts with NO_3^- to form NH_4NO_3.

Below we lay out the specifics of our approach:

Step 1: Calculate the mole ratio of NH_4^+ to SO_4^{2-}.

$R = (\mathrm{NH_4^+}/18.03846)/(\mathrm{SO_4^{2-}}/96.0626)$:

a) If $R < 1$ then we assume that a portion of SO_4^{2-} converts to NH_4HSO_4 ($SO_4^{2-} + NH_4^+ \rightarrow NH_4HSO_4$), while the rest remains as SO_4^{2-}

- Resulting concentration of NH_4HSO_4 is
$15.109 \cdot \min\{(\mathrm{NH_4^+}/18.03846), (\mathrm{SO_4^{2-}}/96.0626)\}$

- Resulting concentration of remaining SO_4^{2-} is
$96.0626 \cdot \left((\mathrm{SO_4^{2-}}/96.0626) - (\mathrm{NH_4^+}/18.03846)\right)$

b) If $1 \leq R < 2$ then we assume that all SO_4^{2-} converts to NH_4HSO_4 ($SO_4^{2-} + NH_4^+ \rightarrow NH_4HSO_4$) and a portion of NH_4HSO_4 converts to $(NH_4)_2SO_4$ ($NH_4HSO_4 + NH_4^+ \rightarrow (NH_4)_2SO_4$). The second reaction will occur if there is enough NH_4^+ remaining after the first reaction.

- Resulting concentration of NH_4HSO_4 is
$115.109 \cdot \left(2(\mathrm{SO_4^{2-}}/96.0626) - (\mathrm{NH_4^+}/18.03846)\right)$

- Resulting concentration of $(NH_4)_2SO_4$ is
$132.13952 \cdot \left((\mathrm{NH_4^+}/18.03846) - (\mathrm{SO_4^{2-}}/96.0626)\right)$

c) If $R \geq 2$ then we assume that all SO_4^{2-} converts to (NH4)2SO4 ($SO_4^{2-} + 2NH_4^+ \rightarrow (NH_4)_2SO_4$).

- Resulting concentration of $(NH_4)_2SO_4$ is
$132.13952 \cdot (\mathrm{SO_4^{2-}}/96.0626)$
- Resulting concentration of NH_4^+ (remaining) is
$18.03846 \cdot \left((\mathrm{NH_4^+}/18.03846) - 2(\mathrm{SO_4^{2-}}/96.0626)\right)$

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:

$$\text{moles of } NO_3^-(\text{neutralized}) = \min\{(NH_4^+(\text{remaining})/18.03846), (NO_3^-/62.0049)\}.$$

Step 3: Particulate NH_4NO_3 is stable at relatively low temperatures. Following prior usage of the S-R Matrix (e.g., NOx 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:

$$80.04336 \cdot 0.25 \cdot \text{moles of } NO_3^-(\text{neutralized}).$$

Step 4: The concentration of $PM_{2.5}$ at the destination county is estimated as the sum of concentrations of primary $PM_{2.5}$, SOA, remaining SO_4^{2-} (if any) and secondary NH_4HSO_4, $(NH_4)_2SO_4$, and NH_4NO_3:

$$\begin{gathered} PM_{2.5}(\text{total}) = PM_{2.5}(\text{primary}) + SOA \\ +SO_4^{2-}(\text{remaining}) \\ +NH_4HSO_4 + (NH_4)_2SO_4 + NH_4NO_3 \end{gathered}$$

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 the 2011 emissions inventory from EPA's 2011v6.2 platform and 2011 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.[21]

First, we used the S-R Matrix with the 2011 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 motoring data to ensure that it did not contain any values flagged as invalid and that minimum number of daily measurements per quarter was 11;[22]

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;

[21] 2011 daily PM2.5 monitoring data from EPA were downloaded at http://aqsdr1.epa.gov/aqsweb/aqstmp/airdata/download_files.html (U.S. EPA, 2011d).
[22] 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.

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 0.16 to 3.53 with a mean value of 0.91. 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:

$$\mathrm{PM}_{2.5}(\text{calibrated model, 2025 or 2017}) = \mathrm{PM}_{2.5}(\text{model, 2025 or 2017}) \cdot \left(\frac{\mathrm{PM}_{2.5}(\text{interpolated monitor, 2011})}{\mathrm{PM}_{2.5}(\text{model, 2011})}\right)$$

To sum up, the steps involved in the calculation of 2017 or 2025 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 2011 are run through the S-R Matrix and atmospheric chemistry calculations applied to generate un-calibrated 2011 model estimates. Monitoring data for 2011 were interpolated to the county-level, and were then compared with the 2011 model estimates to generate calibration factors. Estimates of 2017 or 2025 ambient $PM_{2.5}$ levels can then be generated by running the 2017 or 2025 emissions data through the S-R Matrix. The resulting 2017 or 2025 model $PM_{2.5}$ levels are then multiplied with the previously generated county-level calibration factors to calculate a best estimate of the 2017 or 2025 calibrated ambient $PM_{2.5}$ levels.

Exhibit A-6. Monitor and Model Average $PM_{2.5}$ Levels (ug/m3) in 2011 and Average of Monitor to Model Ratios by State

State	Monitor	Model	Ratio	State	Monitor	Model	Ratio
AL	10.99	16.97	0.65	MT	6.74	4.57	1.47
AZ	7.24	7.53	0.96	NE	7.18	7.44	0.97
AR	11.26	15.38	0.73	NV	8.00	4.70	1.70
CA	8.79	6.79	1.29	NH	7.26	8.66	0.84
CO	5.76	7.30	0.79	NJ	9.61	13.79	0.70
CT	8.91	11.32	0.79	NM	6.59	8.54	0.77
DE	9.74	11.63	0.84	NY	8.31	10.18	0.82
DC	9.97	20.26	0.49	NC	9.77	12.49	0.78
FL	9.32	12.85	0.73	ND	6.04	5.01	1.20
GA	10.98	17.94	0.61	OH	11.05	15.89	0.70
ID	7.66	6.03	1.27	OK	9.90	12.49	0.79
IL	11.45	12.45	0.92	OR	8.01	6.09	1.32
IN	11.59	14.31	0.81	PA	10.22	12.06	0.85
IA	9.91	8.94	1.11	RI	8.53	9.90	0.86
KS	8.51	9.88	0.86	SC	10.49	14.39	0.73
KY	11.22	13.58	0.83	SD	6.31	5.68	1.11

LA	10.32	15.56	0.66	TN	11.09	13.28	0.83
ME	6.55	5.96	1.10	TX	9.52	10.74	0.89
MD	10.05	13.39	0.75	UT	6.54	6.13	1.07
MA	8.31	11.24	0.74	VT	6.86	7.61	0.90
MI	8.04	9.89	0.81	VA	9.74	13.22	0.74
MN	7.60	8.98	0.85	WA	7.95	4.54	1.75
MS	10.81	16.00	0.68	WV	10.61	13.28	0.80
MO	10.88	12.64	0.86	WI	8.54	9.52	0.90
				WY	4.87	6.19	0.79

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 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 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:

$$Cases\ Avoided = \beta \cdot \Delta x \cdot population$$

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 $\alpha = \ln(B)$.[23]

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 –

[23] 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, $B = B_o\exp\{\beta_1 x_1 + ... + \beta_n x_n\}$, where B_o is the incidence of y when all covariates in the model are zero, and $x_1, ... , x_n$ 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.

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, $x = x_{low}$):

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

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

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

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

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

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:

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

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:

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

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 (= Δx), all other covariates held constant, may be derived from the original C-R function above:

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

[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).

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

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

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:

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

It can be shown that:

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

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:

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

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.

[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.

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:

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

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:

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

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

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:

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

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):

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

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 $\mu g/m^3$ for $PM_{2.5}$. However, EPA's most current understanding of the scientific literature is that there is no threshold in the relationship between $PM_{2.5}$ 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 $PM_{2.5}$ co-benefits down to the lowest modeled $PM_{2.5}$ air quality levels.

Following EPA's updated methodology, we also assume there is no threshold for modeling $PM_{2.5}$-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 PM_{10} 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 $\mu g/m^3$ (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 $\mu g/m^3$.

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 NO_2 national ambient air quality standards, U.S. EPA (2009) used Pope et al. (2002)[24] 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

[24] 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 (O_3, SO_4, SO_2, 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-$\mu g/m^3$ 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-$\mu g/m^3$ 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 PM_{10} 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. PM_{10} exposure was significant for all-cause mortality. PM_{10} 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 $\mu g/m^3$ change in PM_{10} (Woodruff et al., 1997, Table 3).

Functional Form: Logistic
Coefficient: 0.003922
Standard Error: 0.001221
Incidence Rate: county-specific annual post-neonatal[25] infant deaths per infant under the age of one
Population: population of infants under one year old

[25] 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).[26] 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 PM_{10}, $PM_{10-2.5}$, $PM_{2.5}$, "black carbon", O_3, CO, NO_2, and SO_2 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 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

[26] 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).

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 $\mu g/m^3$ 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 µg/m3 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 µg/m3 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 cased 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)[27]

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 NO_2 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/m^3 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).

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,

[27] 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.

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/m^3 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/m^3 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 0-17 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 0-17) 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 $\mu g/m^3$ 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 $\mu g/m^3$ 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 $\mu g/m^3$ 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 $\mu g/m^3$ 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, SO_2, NO_2, CO, and PM_{10} 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, SO_2 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 PM_{10} or $PM_{2.5}$. The strongest overall effects were observed for SO_2 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 $\mu g/m^3$ 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 $\mu g/m^3$ increase in 2-day averaged PM2.5 (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 PM2.5 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 $\mu g/m^3$ 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 PM_{10}, $PM_{2.5}$, coarse $PM_{10-2.5}$, SO_2, ozone, and CO in a Poisson regression model with control for time trends,

seasonal variations, and temperature-related weather effects.[28] They found asthma hospital admissions associated with PM_{10}, $PM_{2.5}$, $PM_{10-2.5}$, CO, and ozone. They did not observe an association for SO_2. 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 $\mu g/m^3$ 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 -17[29]

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 $\mu g/m^3$ 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
Incidence Rate: county-specific daily hospital admission rate for asthma admissions per person (ICD-9 code 493)

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[28] $PM_{2.5}$ levels were estimated from light scattering data.
[29] 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 17.

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, SO_2, NO_2, CO, and PM_{10} 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 PM_{10}. 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 $\mu g/m^3$ 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 64[30]

[30] 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 (PM_1, $PM_{2.5}$, PM_{10}, 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 $\mu g/m^3$ 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.[31] 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 PM15. 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.

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

[31] 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.

μg/m3) versus the least polluted city ($PM_{2.1}$ = 5.8 μg/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 in 2010 = 0.043 (American Lung Association, 2013, 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 μg/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.[32] 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. Controlling for ozone, two-week average $PM_{2.5}$ was significantly linked to both health endpoints in most years.[33] The health impact function for $PM_{2.5}$ is based on this co-pollutant model.

[32] 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.
[33] 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.

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 (O_3 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:

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

This 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.[34] The annual national survey results used in this analysis were conducted in 1976-1981. Ostro reported that two-week average $PM_{2.5}$ levels[35] were significantly linked to work-loss days, RADs, and RRADs, however

[34] 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.
[35] 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.

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

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 PM_{10}, $PM_{2.5}$, NO_2, and O_3 in a logistic regression model with control for age, income, time trends, and temperature-related weather effects.[36] 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 PM_{10} and $PM_{2.5}$ and cough incidence associated with $PM_{2.5}$, PM_{10}, and NO_2. 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 $\mu g/m^3$ 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 17 = 10.70%; asthmatic population age 18 = 7.19%.[37]

[36] The authors note that there were 26 days in which $PM_{2.5}$ concentrations were reported higher than PM_{10} 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.
[37] The American Lung Association (2010, Table 7) estimates asthma prevalence for children ages 5-17 at 10.70% and for adults ages 18-44 at 7.19% (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 $\mu g/m^3$ increase in 12-hour average $PM_{2.5}$ 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 17 = 10.70%; asthmatic population age 18 = 7.19%.

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 $\mu g/m^3$ increase in 12-hour average $PM_{2.5}$ 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 17 = 10.70%; asthmatic population age 18 = 7.19%.

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 $PM_{2.5}$. However, the authors found no association between respiratory symptoms and $PM_{2.5}$ 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 $PM_{2.5}$ 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 μg/m3 increase in 1-day lagged concentration of $PM_{2.5}$ (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 17 = 10.70%; asthmatic population age 18 = 7.19%.

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 PM2.5 (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 17 = 10.70%; asthmatic population age 18 = 7.19%.

Upper Respiratory Symptoms (Pope, 1991)

Using logistic regression, Pope et al. (1991) estimated the impact of PM_{10} 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 PM_{10} 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, NO_2, and SO_2 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 PM_{10} significantly associated with both upper and lower respiratory symptoms. The patient-based sample did not find a significant PM_{10} effect. The results from the school-based sample are used here.

The coefficient and standard error for a one $\mu g/m^3$ 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 17 = 10.70% [38] of population ages 9 to 11.

[38] 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 years 2020 and 2025 for use in COBRA.[39] 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 years 2020 and 2025.

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,[40] 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.[41] For each combination of age group and mortality cause, we used the following procedure to deal with the problem of "unreliable" rates:

[39] We use projected 2020 mortality rates for analysis year 2017 in COBRA because the Census Bureau national mortality rates are projected only every 5 years and are not available for 2017.

[40] 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).

[41] Among all the calculated age-, cause-, and county-specific mortality rates, there were about 67% "unreliable" rates.

- 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.[42]

- 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."[43]

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 divided by the sum of the populations in those counties to derive a single rate for the

[42] After this adjustment, there were 17% unreliable rates left.
[43] After this regional adjustment, there were 7% unreliable rates left.

"national collection of counties." This rate was then applied to each of those counties in the "national collection of counties."[44]

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 and 2025

To estimate age- and county-specific mortality rates in years 2020 and 2025, 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.[45]
- We then calculated, separately for each age group, the ratio of Census Bureau national mortality rate in years 2020 and 2025 to the 2005 rate. These ratios are shown in Exhibit D-4.
- Finally, to estimate mortality rates in years 2020 and 2025 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 and 2025 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 and 2025 for ages 18-24 to Census Bureau national mortality rate in 2005 for ages 18-24.

[44] 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."

[45] 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 2025 and 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+
2025	0.78	0.76	0.81	0.85	0.79	0.79	0.82	0.81	0.78	0.87
2020	0.85	0.81	0.86	0.90	0.83	0.85	0.87	0.85	0.83	0.91

Hospitalizations

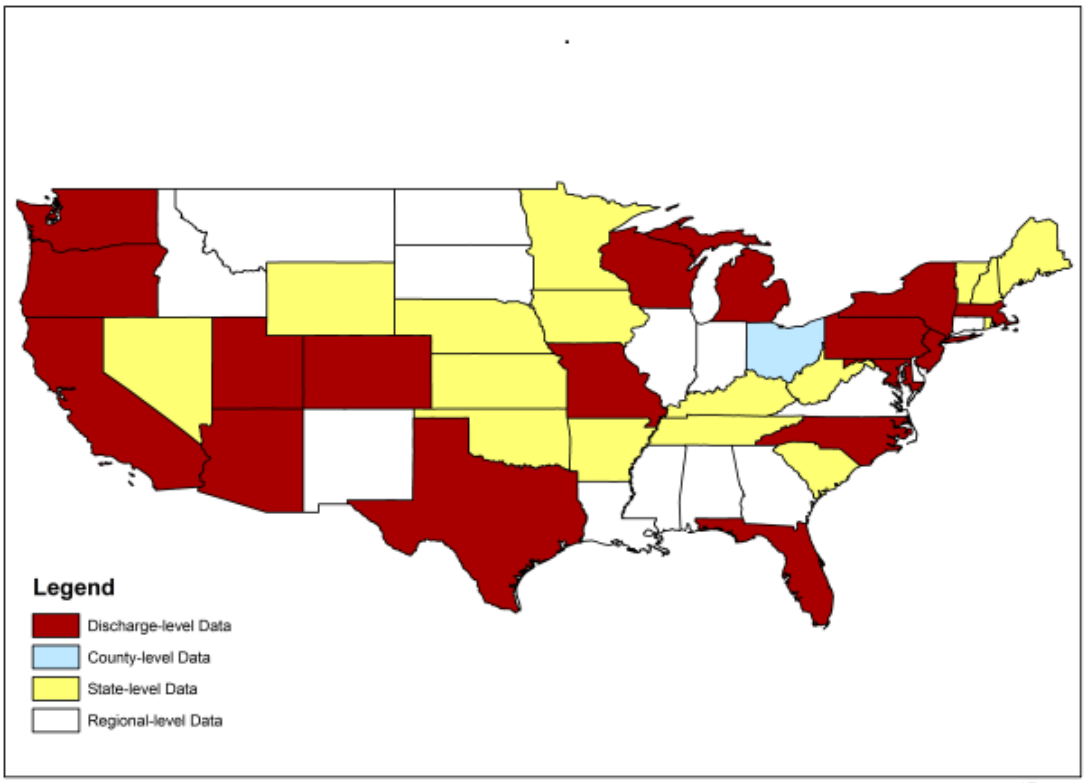
Hospitalization rates were calculated using data from the Healthcare Cost and Utilization Project (HCUP). HCUP is a family of health care databases developed through a Federal-State-Industry partnership and sponsored by the Agency for Healthcare Research and Quality (AHRQ).[46] HCUP products include 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.

[46] 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:[47]

- For states with discharge-level data:
  - We calculated age-, health endpoint-, and county-specific hospitalization counts.48
  - 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.

[47] 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.
[48] 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 ith endpoint in the jth region as "TOTALij").

  - For those states in the jth region that do have discharge-level or state-level data, we summed the hospital admissions by endpoint (we refer to this count for the ith endpoint in the jth region as "SUB ij").

  - We then estimated the hospitalization count for states without discharge or state data for the ith endpoint in the jth region as TOTALij – 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., TOTALij – 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 ith endpoint in the jth 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.

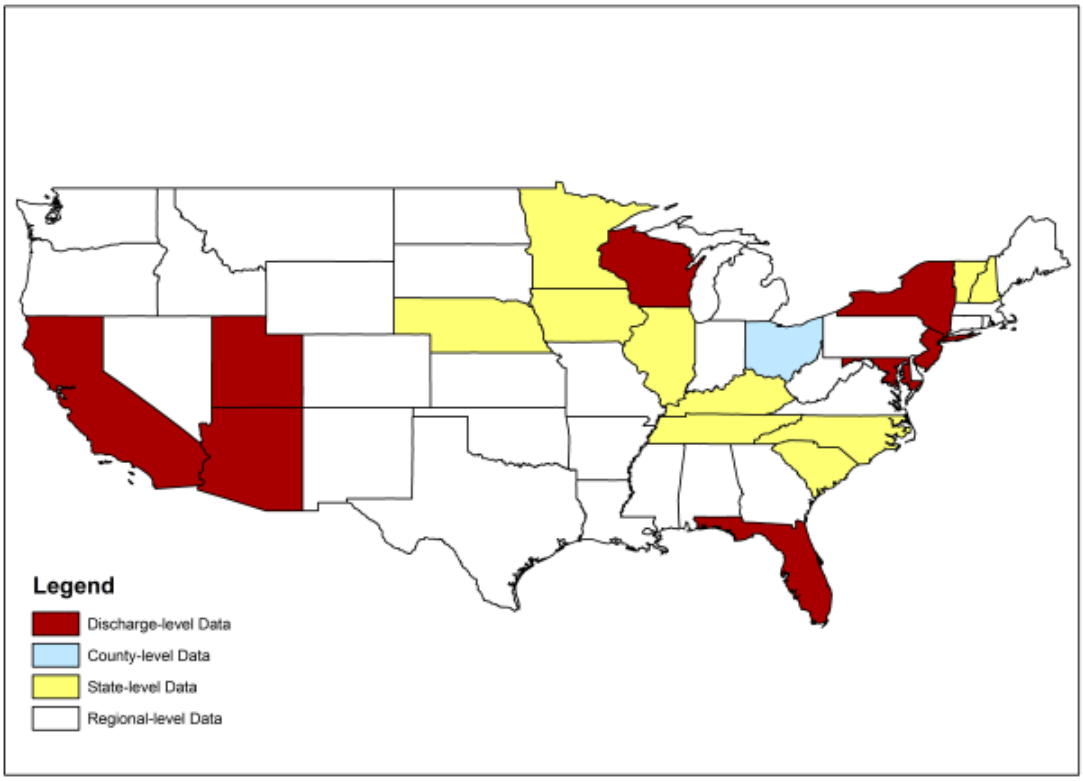
Exhibit D-6. National Hospitalization Rates, by Health Endpoint and Age Group

Hospitalization Category	ICD-9 Codes	Hospitalization Rate by Age Group (admissions per 100 people per year)				
		0-17	18-44	45-64	65-84	85+
Respiratory						
all respiratory	460-519	0.700	0.288	0.995	3.73	8.352
asthma	493	0.173	0.068	0.145	0.216	0.325
chronic lung disease	490-496	0.178	0.089	0.381	1.21	1.598
Cardiovascular						
all cardiovascular (less AMI)	390-409, 411-430	0.019	0.234	1.356	4.974	10.051

Emergency Room Visits for Asthma

The data source for emergency department/room (ED or ER) visits is also HCUP, i.e., SID, SEDD, and NEDS. The types of data providers are also the same as those described above for hospitalizations. Exhibit D-7 shows the emergency department data in each state.

Exhibit D- 7. Emergency Department Data from HCUP



The calculation of ER visit rates is also similar to the calculation of hospitalization rates, except for the following differences:

- 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).[49] We used

[49] 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

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.

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.[50] 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).

[50] 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	6-17	Prevalence	10.70%	(American Lung Association, 2010, Table 7) [c]
	18	Prevalence	7.19%	
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% and for adults ages 18-44 at 7.19% (based on data from the 2008 National Health Interview Survey).

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 years used for COBRA are 2017 and 2025.

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 for 2025 and Exhibit F-2 lists these unit values for 2017.

Exhibit F-1. Unit Values for Economic Valuation of Health Endpoints in 2025 (2017 $)

		Unit Value (2025 Income Level)	
Health Endpoint	**Age Range**	***3% DR***	***7% DR***
Mortality[a]	25 - 99	$9,948,947.61	$8,861,369.71
Infant Mortality[b]	0 - 0	$11,089,231.38	$11,089,231.38
Acute Myocardial Infarction, Nonfatal[c]	0 - 24	$37,333.23	$35,298.14
Acute Myocardial Infarction, Nonfatal[c]	25 - 44	$50,607.91	$47,182.04
Acute Myocardial Infarction, Nonfatal[c]	45 - 54	$56,898.40	$52,813.63
Acute Myocardial Infarction, Nonfatal[c]	55 - 64	$150,418.37	$136,542.02
Acute Myocardial Infarction, Nonfatal[c]	65 - 99	$37,333.23	$35,298.14
Acute Myocardial Infarction, Nonfatal[d]	0 - 24	$183,024.75	$183,024.75
Acute Myocardial Infarction, Nonfatal[d]	25 - 44	$196,298.31	$194,908.66
Acute Myocardial Infarction, Nonfatal[d]	45 - 54	$202,588.80	$200,540.24
Acute Myocardial Infarction, Nonfatal[d]	55 - 64	$296,109.89	$284,269.76
Acute Myocardial Infarction, Nonfatal[d]	65 - 99	$183,024.75	$183,024.75
HA, All Cardiovascular (less AMI)	18 - 64	$45,301.86	$45,301.86
HA, All Cardiovascular (less AMI)	65 - 99	$42,493.36	$42,493.36
HA, All Respiratory	65 - 99	$35,639.38	$35,639.38
HA, Asthma	0 - 17	$16,793.72	$16,793.72
HA, Chronic Lung Disease	18-64	$22,159.27	$22,159.27
Asthma ER Visits (Smith et al. (1997)	0 - 99	$520.84	$520.84
Asthma ER Visits (Stanford et al. (1999)	0 - 99	$435.53	$435.53
Acute Bronchitis	8 - 12	$544.41	$544.41
Lower Resp. Symptoms	7 - 14	$23.57	$23.57
Upper Resp. Symptoms	9 - 11	$38.17	$38.17
MRAD	18 - 64	$77.45	$77.45
Work Loss Days	18 - 64	$179.60	$179.60
Asthma Exacerbation (Cough, Shortness of Breath, or Wheeze)	6 - 18	$65.11	$65.11

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)

Exhibit F-2. Unit Values for Economic Valuation of Health Endpoints in 2017 (2017 $)

Health Endpoint	Age Range	Unit Value (2017 Income Level) *3% DR*	*7% DR*
Mortality[a]	25 - 99	$9,468,202.19	$8,433,177.49
Infant Mortality[b]	0 - 0	$10,553,385.80	$10,553,385.80
Acute Myocardial Infarction, Nonfatal[c]	0 - 24	$37,333.23	$35,298.14
Acute Myocardial Infarction, Nonfatal[c]	25 - 44	$50,607.91	$47,182.04
Acute Myocardial Infarction, Nonfatal[c]	45 - 54	$56,898.40	$52,813.63
Acute Myocardial Infarction, Nonfatal[c]	55 - 64	$150,418.37	$136,542.02
Acute Myocardial Infarction, Nonfatal[c]	65 - 99	$37,333.23	$35,298.14
Acute Myocardial Infarction, Nonfatal[d]	0 - 24	$183,024.75	$183,024.75
Acute Myocardial Infarction, Nonfatal[d]	25 - 44	$196,298.31	$194,908.66
Acute Myocardial Infarction, Nonfatal[d]	45 - 54	$202,588.80	$200,540.24
Acute Myocardial Infarction, Nonfatal[d]	55 - 64	$296,109.89	$284,269.76
Acute Myocardial Infarction, Nonfatal[d]	65 - 99	$183,024.75	$183,024.75
HA, All Cardiovascular (less AMI)	18 - 64	$46,024.75	$46,024.75
HA, All Cardiovascular (less AMI)	65 - 99	$43,348.71	$43,348.71
HA, All Respiratory	65 - 99	$36,702.38	$36,702.38
HA, Asthma	0 - 17	$17,320.18	$17,320.18
HA, Chronic Lung Disease	18-64	$22,841.75	$22,841.75
Asthma ER Visits (Smith et al. (1997)	0 - 99	$520.84	$520.84
Asthma ER Visits (Stanford et al. (1999)	0 - 99	$435.53	$435.53
Acute Bronchitis	8 - 12	$535.43	$535.43
Lower Resp. Symptoms	7 - 14	$23.57	$23.57
Upper Resp. Symptoms	9 - 11	$37.04	$37.04
MRAD	18 - 64	$76.33	$76.33
Work Loss Days	18 - 64	$179.60	$179.60
Asthma Exacerbation (Cough, Shortness of Breath, or Wheeze)	6 - 18	$63.98	$63.98

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 2017. To allow for the effect of inflation, we have adjusted these values to reflect prices in 2017$. 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-3 summarizes the types of inflation indices and their sources used to adjust different types of unit values in COBRA.

Exhibit F-3. 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.[51] 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-4).

Exhibit F-4. 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 2025.

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

[51] Details of the procedure can be found in Kleckner and Neumann 1999.

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,[52] the mean value of avoiding one statistical death is estimated to be roughly $11.1 million in 2025 (2017$ at 2025 income level) and $10.6 million in 2017 (2017$ 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,

[52] 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.

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 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, the Wittels et al. estimate is $183,023 in year 2017$. 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 $83,009 in 2017$ 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 $1,051 annually thereafter. Converting to year 2017$, that would be $37,334 (3% discount rate) and $35,298 (7% discount rate) for a 5-year period.

As seen in Exhibit F-5, 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-6 gives the resulting estimates.

Exhibit F-5. Summary of Studies Valuing Reduced Incidences of Myocardial Infarction

Study	Direct Medical Costs (2017 $, 3% DR)	Direct Medical Costs (2017 $, 7% DR)	Over an x-year period, for x =
Wittels et al., 1990[a]	$183,024	$183,024	5
Russell et al., 1998	$37,334	$35,298	5
Eisenstein et al., 2001	$83,009	$83,009	10

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

Exhibit F-6. Estimated Costs Over a 5-Year Period of a Non-Fatal Myocardial Infarction

Age Group	Opportunity Cost (2017 $, 3% DR) [a]	Opportunity Cost (2017 $, 7% DR) [a]	Medical Cost (2017 $, 3% DR) [b]	Medical Cost (2017 $, 7% DR) [b]	Total Cost (2017 $, 3% DR)	Total Cost (2017 $, 7% DR)
0 - 24	$0	$0	$110,178	$109,160	$110,178	$109,160
25-44	$13,273	$11,883	$110,178	$109,160	$123,452	$121,044
45 - 54	$19,564	$17,516	$110,178	$109,160	$129,743	$126,677
55 - 65	$113,085	$101,245	$110,178	$109,160	$223,264	$210,405
> 65	$0	$0	$110,178	$109,160	$110,178	$109,160

[a] From Cropper and Krupnick (1990). Present discounted value of 5 years of lost earnings, adjusted from 1977$ to 2017$ using CPI.
[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.

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.[53]

[53] 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

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 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 annual wages for 2010 were obtained from the U.S. Census Bureau, 2010 American Community Survey, 1-year estimates, Table B20017: "Median earnings in the past 12 months (in 2010 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". The median daily wage was calculated as the simple average of full-time male earnings ($46,500) and full-time female earnings ($36,551), divided by 52 × 5, resulting in an estimate of $159.7.

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

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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.

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 $521 in 2017$. The second is from Stanford et al. (1999), who examined data from asthmatics from 1996-1997, and reported an average cost of $436 (2017$). We use a simple average of the two estimates, which yields a unit value of about $478 (2017$).

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 × 6), $535 in 2017$ and at 2017 income level, or $544 in 2017$ and at 2025 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 for 2025 and in F-9 for 2017.

The three individual symptoms listed in Exhibit F-7 and Exhibit F-9 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 for 2025 and Exhibit F-10 for 2017. We assumed that each of these seven complexes is equally likely.[54] The point estimate of WTP is just an average of the seven estimates of WTP for the different complexes.

A unit value of $37.68 in 2025 (at 2025 income level and in 2017$) and $37.03 in 2017 (at 2017 income level and in 2017$) assumes that an episode of the symptoms lasts only one day.

Exhibit F-7. Median WTP Estimates and Derived Midrange Estimates (2025 income level, 2017 $)[a]

Symptom [b]	Dickie et al. (1987)	Tolley et al. (1986)	Loehman et al. (1979)	Mid-Range Estimate
Throat congestion	7.61	32.95	-	20.16
Head/sinus congestion	8.88	35.48	16.51	20.16
Coughing	2.54	27.91	10.04	14.12
Eye irritation	-	-	-	-
Headache	2.54	50.70	-	20.161
Shortness of breath	0-	-	21.28	10.06
Pain upon deep inhalation (PDI)	8.90	-	-	8.90
Wheeze	5.08	-	-	5.08
Coughing up phlegm	5.54[c]	-	-	5.54
Chest tightness	12.70	-	-	12.70

[a] Values were inflated to 2017 $ using CPI and adjusted to 2025 income level.

[b] All estimates are WTP to avoid one day of symptom. Midrange estimates were derived by IEc (1993).

[c] 10% trimmed mean.

[54] 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.

Exhibit F-8. Estimates of WTP to Avoid Upper Respiratory Symptoms (2025 income level, 2017 $)[a]

Symptom Combinations Identified as URS by Pope et al. (1991)	WTP to Avoid Symptom(s)
Coughing	$14.12
Head/Sinus Congestion	$20.16
Eye Irritation	$31.65
Coughing, Head/Sinus Congestion	$34.27
Coughing, Eye Irritation	$45.78
Head/Sinus Congestion, Eye Irritation	$51.81
Coughing, Head/Sinus Congestion, Eye Irritation	$65.92
	Average:$37.67

[a] Values were inflated to 2017$ and adjusted to 2025 income level.

Exhibit F-9. Median WTP Estimates and Derived Midrange Estimates (2017 income level, 2017$)[a]

Symptom [b]	Dickie et al. (1987)	Tolley et al. (1986)	Loehman et al. (1979)	Mid-Range Estimate
Throat congestion	0.00	0.00	0.00	0.00
Head/sinus congestion	7.48	32.38	-	19.81
Coughing	8.72	34.88	16.23	19.81
Eye irritation	2.49	27.42	9.87	13.87
Headache	-	31.12	-	31.12
Shortness of breath	2.49	49.84	-	19.81
Pain upon deep inhalation (PDI)	0.00	-	20.92	9.89
Wheeze	8.74	-	-	8.74
Coughing up phlegm	5.00[c]	-	-	5.00
Chest tightness	5.46	-	-	5.46

[a] Values were inflated to 2017 $ using CPI 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-10. Estimates of WTP to Avoid Upper Respiratory Symptoms (2017 income level, 2017 $)[a]

Symptom Combinations Identified as URS by Pope et al. (1991)	WTP to Avoid Symptom(s)
Coughing	$13.87
Head/Sinus Congestion	$19.81
Eye Irritation	$31.12
Coughing, Head/Sinus Congestion	$33.69
Coughing, Eye Irritation	$44.99
Head/Sinus Congestion, Eye Irritation	$50.93
Coughing, Head/Sinus Congestion, Eye Irritation	$64.80
	Average: $37.03

[a] Values were inflated to 2017 $ 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.[55] We assumed that each of the eleven types of lower respiratory symptoms is equally likely,[56] and the mean WTP is the average of the WTPs over all combinations. Exhibit F-11 presents resulting estimates in 2025 and Exhibit F-12 presents resulting estimates in 2017.

[55] 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.

[56] 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.

Exhibit F-11. Estimates of WTP to Avoid Lower Respiratory Symptoms (2025 income level and 2017 $)

Symptom Combinations Identified as LRS by Schwartz et al. (1994, p. 1235)	WTP to Avoid Symptoms
Coughing, Chest Tightness	$26.79
Coughing, Coughing Up Phlegm	$19.64
Coughing, Wheeze	$19.17
Chest Tightness, Coughing Up Phlegm	$18.23
Chest Tightness, Wheeze	$17.77
Coughing Up Phlegm, Wheeze	$10.63
Coughing, Chest Tightness, Coughing Up Phlegm	$32.35
Coughing, Chest Tightness, Wheeze	$31.89
Coughing, Coughing Up Phlegm, Wheeze	$24.74
Chest Tightness, Coughing Up Phlegm, Wheeze	$23.33
Coughing, Chest Tightness, Coughing Up Phlegm, Wheeze	$37.42
	Average: $23.82

Exhibit F-12. Estimates of WTP to Avoid Lower Respiratory Symptoms (2017 income level and 2017 $)

Symptom Combinations Identified as LRS by Schwartz et al. (1994, p. 1235)	WTP to Avoid Symptoms
Coughing, Chest Tightness	$26.33
Coughing, Coughing Up Phlegm	$19.31
Coughing, Wheeze	$18.85
Chest Tightness, Coughing Up Phlegm	$17.92
Chest Tightness, Wheeze	$17.47
Coughing Up Phlegm, Wheeze	$10.45
Coughing, Chest Tightness, Coughing Up Phlegm	$31.80
Coughing, Chest Tightness, Wheeze	$31.34
Coughing, Coughing Up Phlegm, Wheeze	$24.31
Chest Tightness, Coughing Up Phlegm, Wheeze	$22.92
Coughing, Chest Tightness, Coughing Up Phlegm, Wheeze	$36.78
	Average: $23.41

Valuing Work Loss Days (WLDs)

Willingness to pay to avoid the loss of one day of work was estimated by dividing median annual earnings ($46,621 in 2017$) by (52 × 5), which resulted a unit value of $179 (2017$). 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 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 $77 in 2025 (2025 income level and 2017$) and $76 in 2017 (2017 income level and 2017$). 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

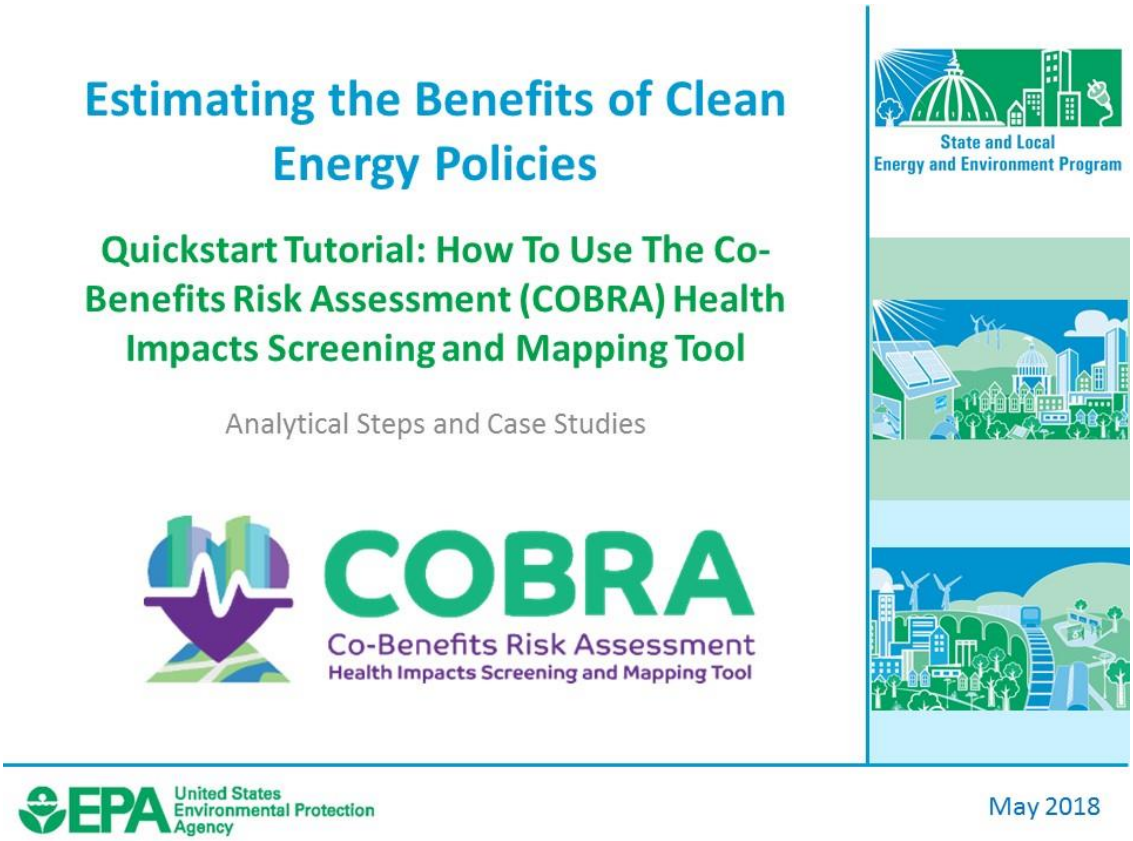
sufficient to result in a MRRAD, so that WTP to avoid a MRRAD should exceed WTP to avoid any single mild symptom. A single severe symptom or a combination of symptoms could, however, be sufficient to restrict activity. Therefore WTP to avoid a MRRAD should, these authors argue, not necessarily exceed 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 $65.45 (2025 income level and 2017$) and $64.54 (2017 income level and 2017$) per incidence in 2025 and 2017, respectively.

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.



Overview of Presentation

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

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How to Conduct an Analysis with COBRA

Analytical Steps and Relevant Resources

State and Local Energy and Environment Program

COBRA
Co-Benefits Risk Assessment
Health Impacts Screening and Mapping Tool

United States Environmental Protection Agency

Steps in COBRA Analysis

1. Select the Analysis Year
2. Create Emission Scenario
   - Estimate where (e.g., in one or more counties or states, regionally, nationally) and what emission changes will take place
   - Enter the location, types, and quantity of emission changes expected from the policy or activity in COBRA
3. Execute Run
   - Select a discount rate in COBRA to appropriately discount the value of future benefits
   - Run the model
4. View Health Effects and Valuation Results
   - 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: Select Analysis Year

- COBRA contains detailed 2017 and 2025 baseline emissions data for each county
- 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 information about the NEI, see: https://www.epa.gov/air-emissions-inventories/national-emissions-inventory-nei

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Step 2: Create Emissions Scenario

Estimate where and what emissions changes 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 https://www.epa.gov/sites/production/files/2015-08/documents/epa_assessing_benefits.pdf

6

Step 2: Create Emissions Scenario

Estimate where and what emissions changes will take place (cont'd)

- 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, if the use of renewable electricity generation increases from 0% to 20% of total generation, 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

7

Resources for Calculating Emissions Changes 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) https://www.epa.gov/energy/emissions-generation-resource-integrated-database-egrid, or
    - EPA's AVoided Emissions and geneRation Tool (AVERT) https://www.epa.gov/statelocalenergy/avoided-emissions-and-generation-tool-avert
  - More sophisticated approaches, such as those described in EPA guides:
    - *Assessing the Multiple Benefits of Clean Energy: A Resource for States*, Chapter 4 https://www.epa.gov/sites/production/files/2015-08/documents/epa_assessing_benefits.pdf
    - *Roadmap for Incorporating Energy Efficiency/Renewable Energy Policies and Programs into State and Tribal Implementation Plans,* Appendix I https://www.epa.gov/sites/production/files/2016-05/documents/appendixi_0.pdf

8

Step 2: Create Emissions Scenario

Select and enter the types, location and quantity of emission changes expected

- There are two methods for entering emissions changes into COBRA:
  1. You can enter emissions changes *manually* or
  2. You can *import an emissions scenario of your own,* such as an automatically pre-formatted output file from EPA's AVoided Emissions and generRation Tool (AVERT)

9

Step 2: Create Emissions Scenario

Select and enter the types, location and quantity of emission changes expected – manual entry

- You will need to know what source categories of emissions will be affected by the policy
- 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 changes by the appropriate types and locations, ensuring that you save your inputs once you are finished

10

Step 2: Create Emissions Scenario

Select and enter the types, location and quantity of emission changes expected – AVERT output

- As an alternative to manually entering the emissions reductions and locations, you can import the results from EPA's AVERT tool into COBRA.
- After running AVERT, you can export your results in a format that can be imported by COBRA.
- In the "Create Emissions Scenario" tab in COBRA, you can click "Load AVERT output file" to import the AVERT file.
- These steps are explained in more detail in Case Study #2, below.

For more details, EPA's AVERT tool and documentation are available at https://www.epa.gov/statelocalenergy/avoided-emissions-and-generation-tool-avert .

11

Step 3: Execute Run

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

12

Step 3: Execute Run

Select a discount rate (cont'd)

- 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 benefits which occur in the future
- 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 3: Execute Run

Run the model

- Once you have completed these four steps, you are ready to run the model
- The model will take at least five minutes to run and may take longer, depending on the speed of your computer
- The model may appear non-responsive while it is processing

14

Step 4: View Health Effects and Valuation Results

- 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 (cont'd)

- 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 (cont'd)

- COBRA does not account for changes in emissions that can result from changes in electricity market responses to policy.
  - For example, emissions in some states and regions are "capped" by laws or regulations
    - Emission allowances can then be traded across entities within a capped region
    - In these regions, a reduction in emissions in one location may result in an increase (rebound) in emissions in another area subject to the cap
    - COBRA does not automatically capture these types of potential effects in electricity market dispatch
- Care should be exercised when interpreting COBRA results to analyze the net impacts of a change in policy

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Case Study 1: Renewable Portfolio Standard

State and Local Energy and Environment Program

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

COBRA
Co-Benefits Risk Assessment
Health Impacts Screening and Mapping Tool

United States Environmental Protection Agency

Analyzing the Health Benefits of a Renewable Portfolio Standard

- 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

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Analyzing the Health Benefits of a Renewable Portfolio Standard (cont'd)

- 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 2025
    - We also could have looked at a county with a renewable target or requirement

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Step 1: Select the Analysis Year

22

Step 2: Create Emissions Scenario

Estimate where and what emissions changes 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 2: Create Emissions Scenario

Estimate where and what emissions changes will take place (cont'd)

- 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 2: Create Emissions Scenario

Estimate where and what emissions changes will take place (cont'd)

- 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 2: Create Emissions Scenario

Estimate where and what emissions changes will take place (cont'd)

- For this example, we use emissions factors from EPA's Emissions & Generation Resource Integrated Database (eGRID)* to develop an absolute estimate
  - Using "eGRID2014 Summary Tables (PDF)," we found:
    - Net electric generation in Michigan: **107 million MWh**
    - Non-baseload output emissions rates for Michigan:

      SO_2: **4.1 lbs. per MWh**

      NO_x: **1.5 lbs. per MWh**
    - Percentage of electric generation that already comes from renewable sources in Michigan: **7.0%**

* eGRID is available at https://www.epa.gov/energy/emissions-generation-resource-integrated-database-egrid

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Step 2: Create Emissions Scenario

Estimate where and what emissions changes will take place (cont'd)

- Since 7.0% of electric generation already comes from renewable sources, we assume our scenario will reduce emissions by:

  10.0% - 7.0% = **3.0%**
- We calculate the reduction in MWh:

  3.0% × 107 million MWh = **3.2 million MWh**
- Assuming the renewable energy used does not emit any air pollution, we calculate the emission reductions as:

  SO_2: 3.2 million MWh × 4.1 per MWh = 13 million lbs.

  = **6,600 tons**

  NO_x: 3.2 million MWh × 1.5 per MWh = 4.8 million lbs.

  = **2,400 tons**

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

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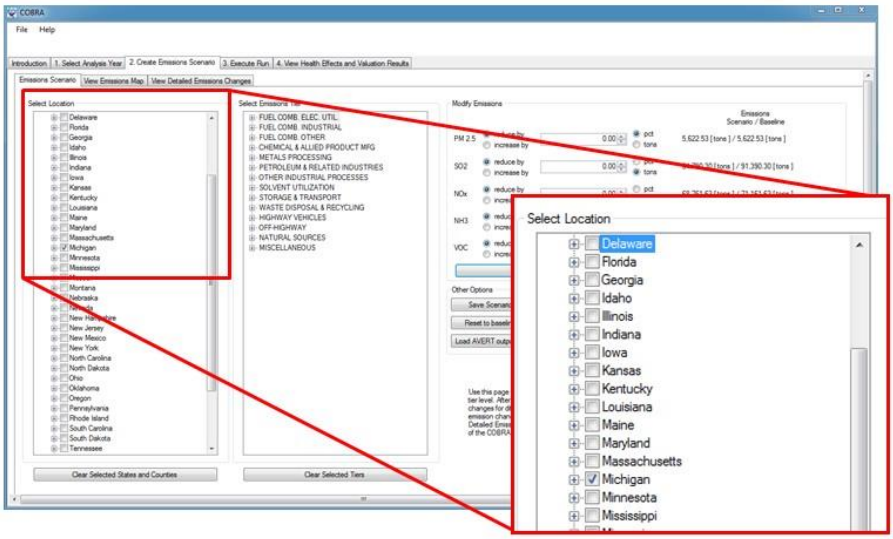
Step 2: Create Emissions Scenario

Select Location of emission changes expected



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Step 2: Create Emissions Scenario

Enter types of emission changes 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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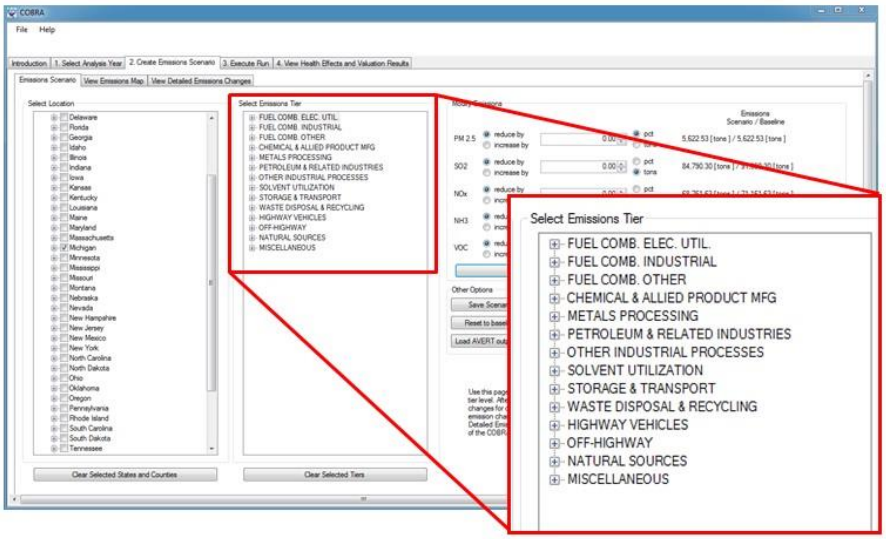
Step 2: Create Emissions Scenario

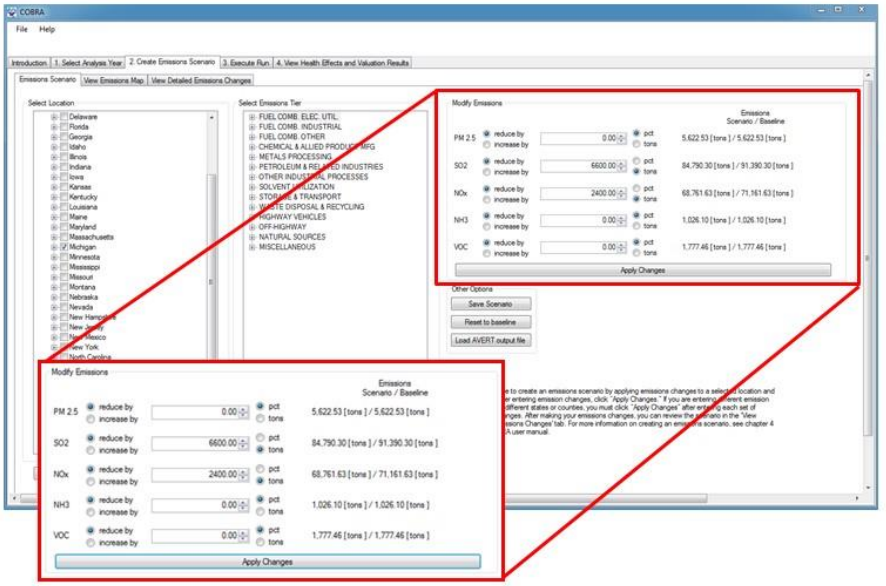
Enter types of emission changes expected



30

Step 2: Create Emissions Scenario

Quantity of emission changes expected



31

Step 3: Execute Run

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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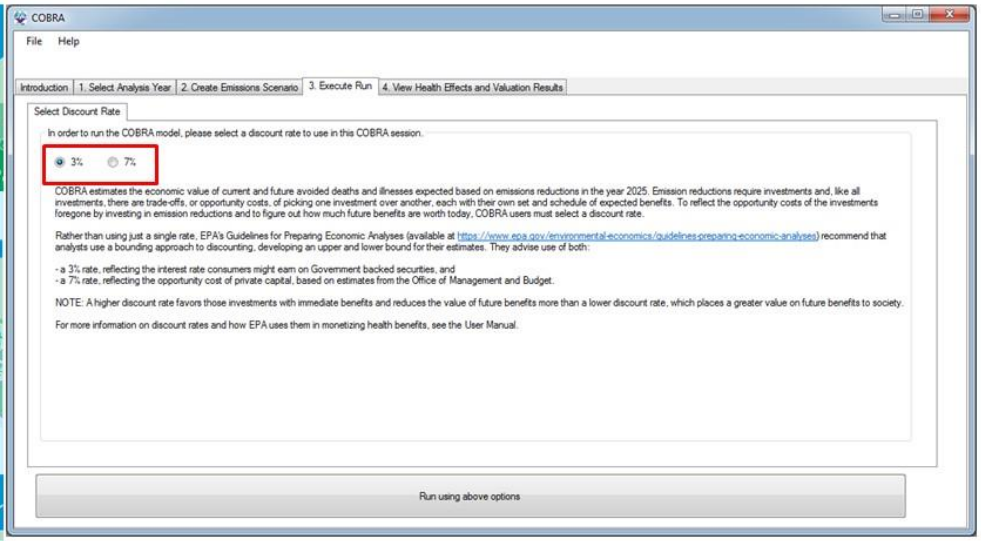
Step 3: Execute Run

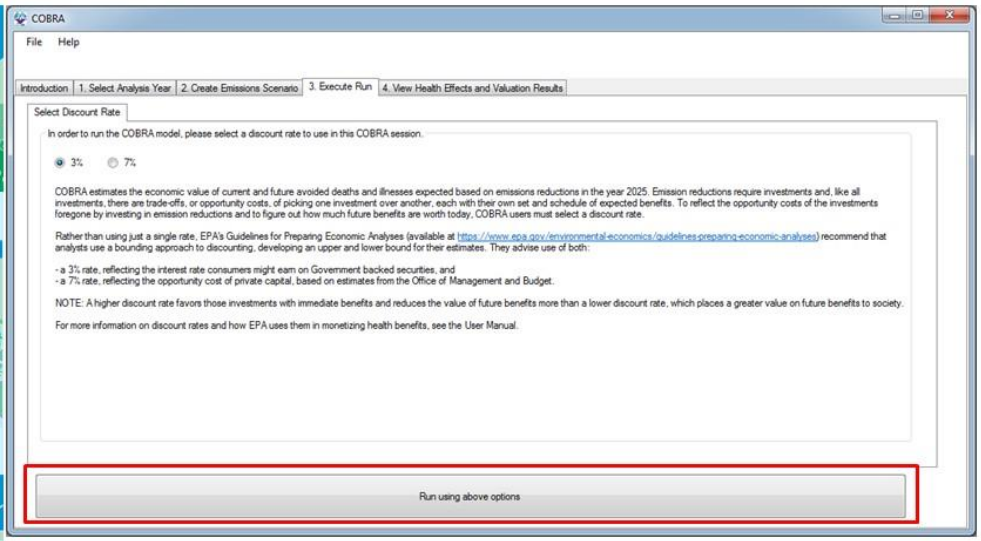
Select a discount rate (cont'd)



33

Step 3: Execute Run

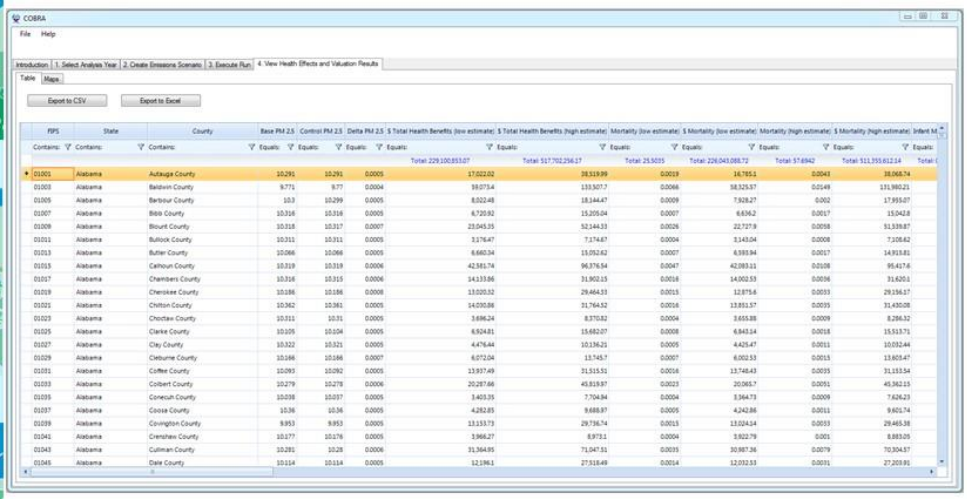
Run the model



34

Step 4: View Health Effects and Valuation Results

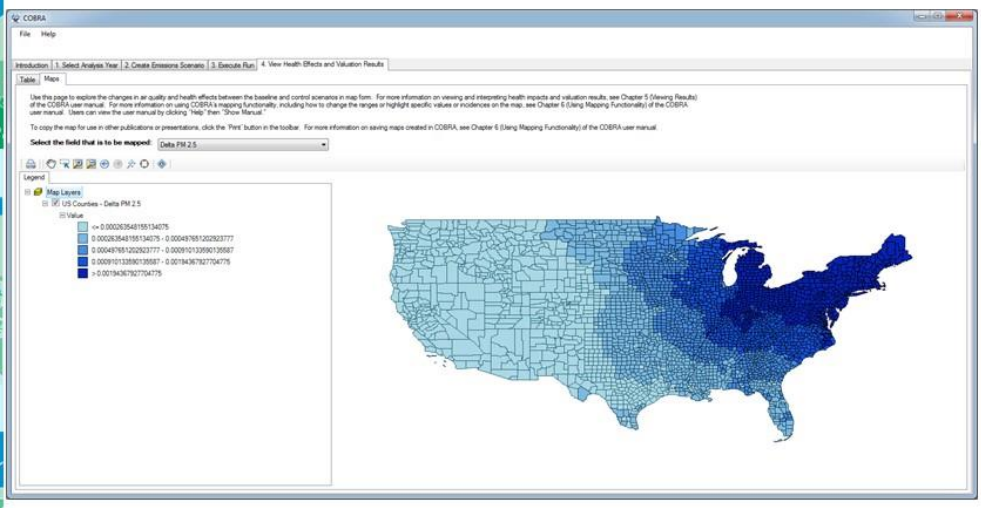
View in table form



35

Step 4: View Health Effects and Valuation Results

View in map form



Step 4: View Health Effects and Valuation Results

We calculated absolute emissions reductions of Michigan's renewable portfolio standard of 10%.

COBRA (1) converted emissions reductions into air quality improvements, and (2) estimated annual adverse health impacts avoided.

COBRA monetized the value or benefits of the avoided adverse health effects.

Annual Emission Reductions (short tons)

Pollutant	Amount
Sulfur Dioxide (SO_2)	6,600
Nitrogen Oxides (NO_x)	2,400

Annual Adverse Health Impacts Avoided

Outcome	Number	Annual Benefits (2017, $1,000s) Dollar Value
Mortality	25.5 – 57.7	$254,000 – $574,000
Asthma Exacerbations	625	$40.9
Heart Attacks	3.3 – 31.0	$445– $4,140
Hospital Admissions	17.4	$659
Acute Bronchitis	33.1	$18.0
Respiratory Symptoms	1,027	$32.8
Asthma ER Visits	13.0	$6.21
Minor Restricted Activity Days	16,600	$1,290
Work Days Lost	2,800	$502
total		$257,000 - $581,000

* Don't forget to consider the caveats from slides 16 through 18

Case Study 2: Wind Energy Program

State and Local Energy and Environment Program

This case study illustrates how to conduct an analysis of a clean energy program with COBRA using wind energy capacity as an example.

COBRA
Co-Benefits Risk Assessment
Health Impacts Screening and Mapping Tool

EPA United States Environmental Protection Agency

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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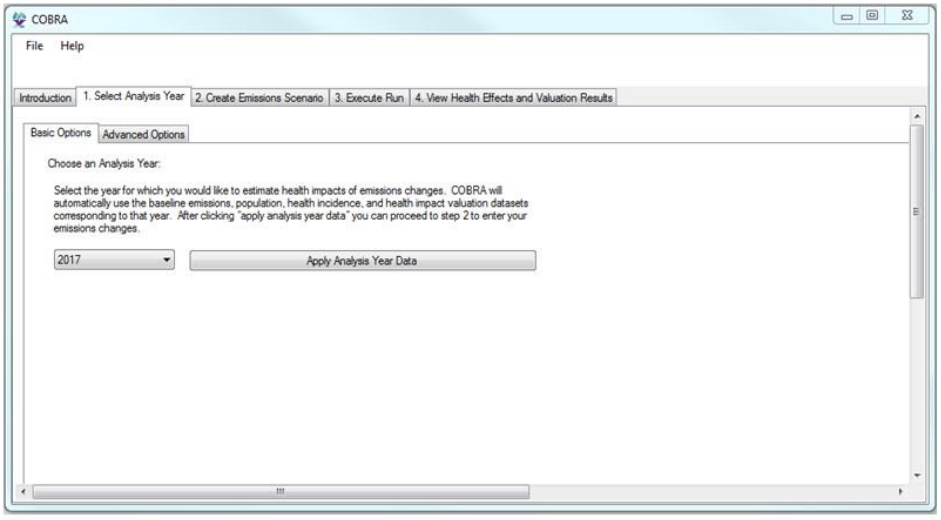
Using COBRA to Evaluate the Benefits of Wind Energy Production (cont'd)

- 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

40

Step 1: Select the Analysis Year



41

Step 2: Create Emissions Scenario

Estimate where and what emissions changes 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

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Step 2: Create Emissions Scenario

Estimate where and what emissions changes will take place (cont'd)

- 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 2: Create Emissions Scenario

Estimate where and what emissions changes will take place (cont'd)

- To estimate the electricity changes expected from the program, you can either:
  - Estimate how many MWh you expect to save from your program, 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 2: Create Emissions Scenario

Estimate where and what emissions changes will take place (cont'd)

- To estimate the annual emissions reduced from 7,000 MW of installed wind capacity, you can use:
  - A basic tool that estimates emissions changes from renewable energy programs
  - A more sophisticated modeling approach, if available

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Step 2: Create Emissions Scenario

Estimate where and what emissions changes will take place (cont'd)

- 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
  - Generate a COBRA input text file in AVERT, which also convert emissions reductions to tons

For more details, EPA's AVERT tool and documentation are available at https://www.epa.gov/statelocalenergy/avoided-emissions-and-generation-tool-avert .

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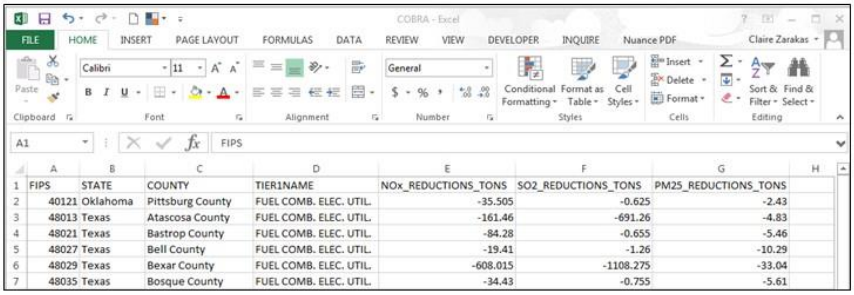
Step 2: Create Emissions Scenario

Estimate where and what emissions changes will take place (cont'd)

- Annual emission reductions (in tons) from a 7,000 MW wind energy program in Texas using AVERT:

State/County	SO_2	NO_x	$PM_{2.5}$
Texas	17,211.7	6,756.7	846.5
Oklahoma*	0.6	35.5	2.4

*Note that Oklahoma also experiences emissions reductions from the wind program in Texas.



FIPS	STATE	COUNTY	TIER1NAME	NOx_REDUCTIONS_TONS	SO2_REDUCTIONS_TONS	PM25_REDUCTIONS_TONS
40121	Oklahoma	Pittsburg County	FUEL COMB. ELEC. UTIL.	-35.505	-0.625	-2.43
48013	Texas	Atascosa County	FUEL COMB. ELEC. UTIL.	-161.46	-691.26	-4.83
48021	Texas	Bastrop County	FUEL COMB. ELEC. UTIL.	-84.28	-0.655	-5.46
48027	Texas	Bell County	FUEL COMB. ELEC. UTIL.	-19.41	-1.26	-10.29
48029	Texas	Bexar County	FUEL COMB. ELEC. UTIL.	-608.015	-1108.275	-33.04
48035	Texas	Bosque County	FUEL COMB. ELEC. UTIL.	-34.43	-0.755	-5.61

Sample AVERT output file for the Texas region

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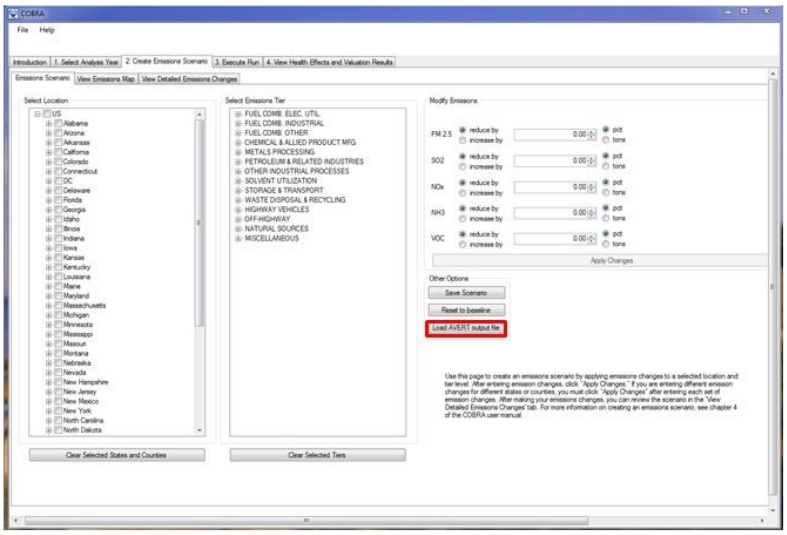
Step 2: Create Emissions Scenario

Import AVERT emissions scenario

- After applying 2017 baseline, click "Load AVERT output file"



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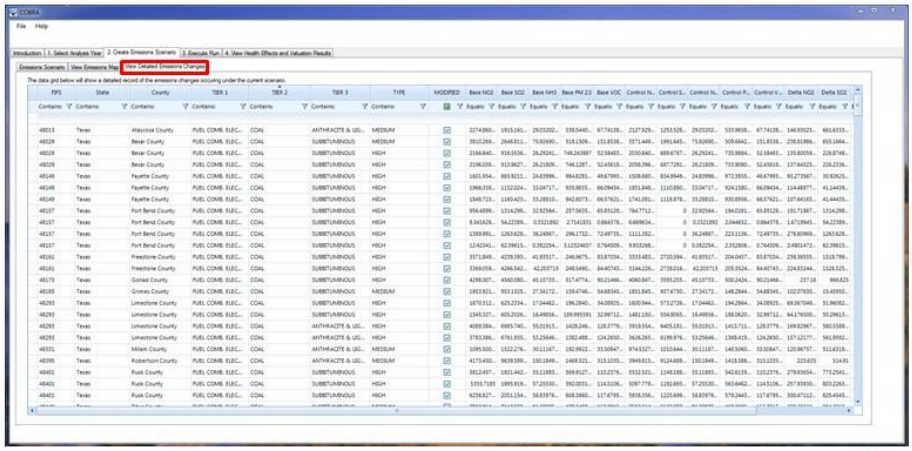
Step 2: Create Emissions Scenario

View Detailed Emissions Changes

- The AVERT scenario includes changes to the "fuel combustion from electricity generation" emissions category



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Step 3: Execute Run

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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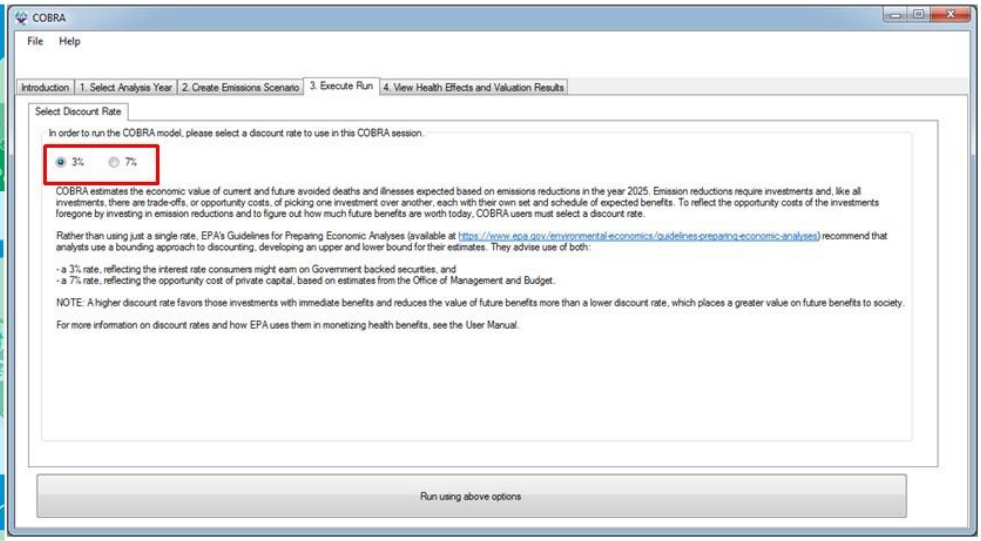
Step 3: Execute Run

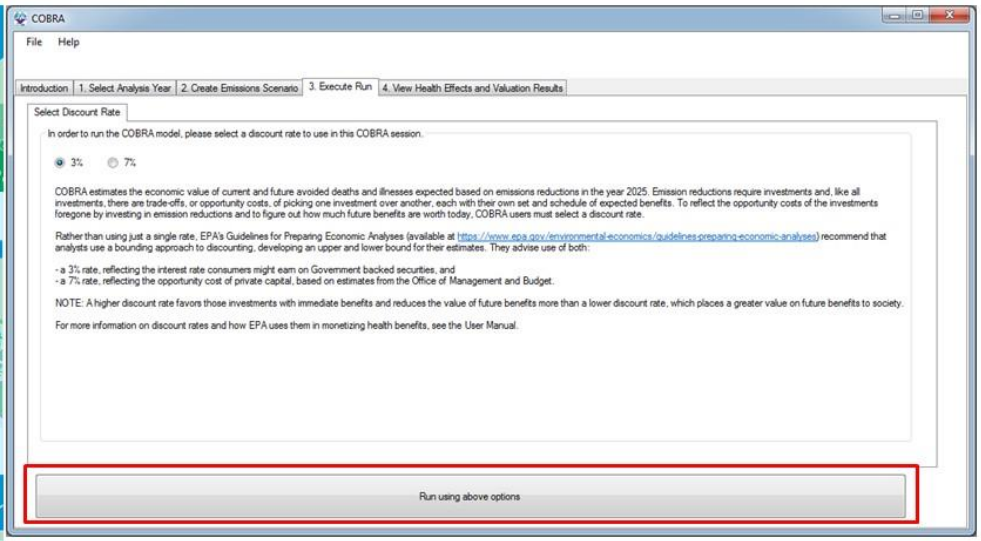
Select a discount rate (cont'd)



51

Step 3: Execute Run

Run the model



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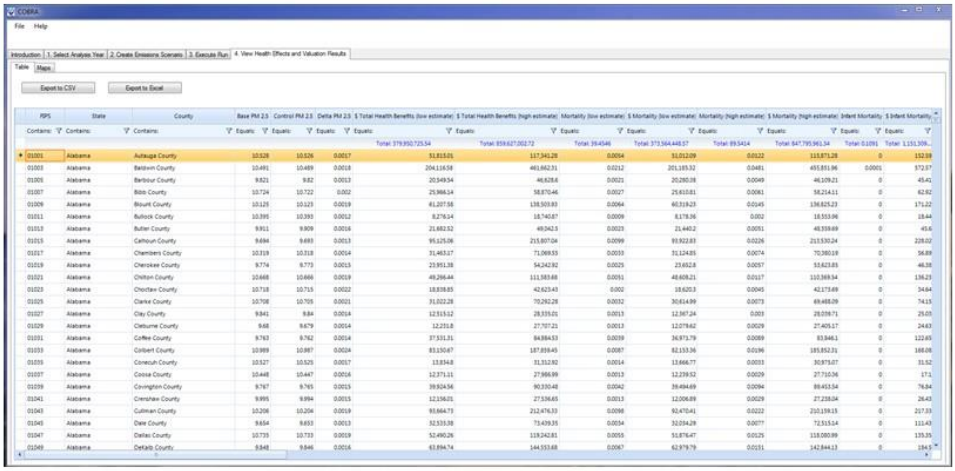
Step 4: View Health Effects and Valuation Results

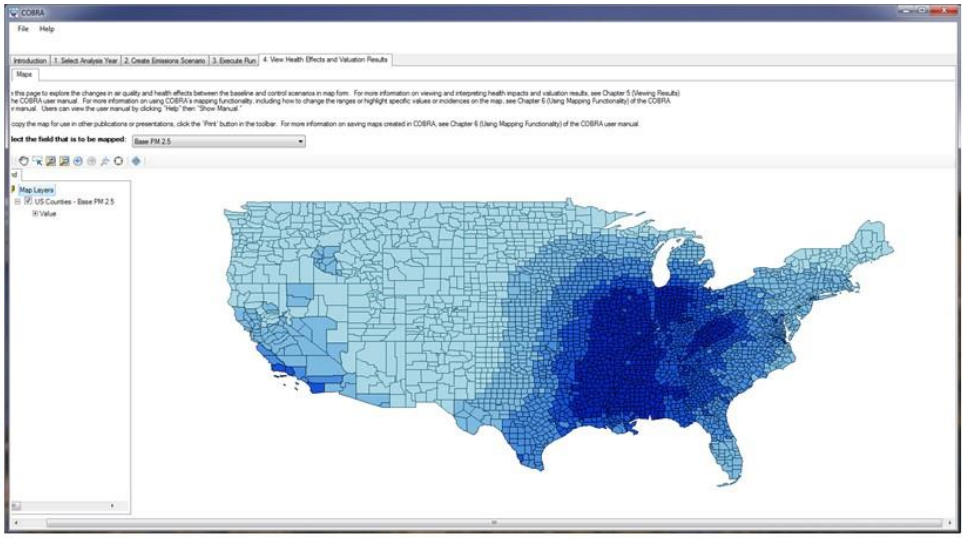
View in table form



53

Step 4: View Health Effects and Valuation Results

View in map form



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Step 4: View Health Effects and Valuation 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)	16,180
Nitrogen Oxides (NO_x)	6,749

Note: These reductions are aggregated across all affected states.

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	39 - 90
Asthma Exacerbations	1,281
Heart Attacks	5 - 44
Hospital Admissions	25
Acute Bronchitis	68
Respiratory Symptoms	2,120
Asthma ER Visits	21
Minor Restricted Activity Days	32,331
Work Days Lost	5,443

COBRA monetized the value or benefits of the avoided adverse health effects.

Annual Benefits (2017, $1,000s)

Dollar Value
$37,564 - $847,796
$82
$657 - $6,101
$950
$37
$66
$10
$2,457
$976
$379,951 - $859,672

total

* Don't forget to consider the caveats from slides 16 through 18

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How Can I Learn More?

Visit Our Website:

https://www.epa.gov/statelocalenergy/co-benefits-risk-assessment-cobra-screening-model

Contact Us:

Denise Mulholland
EPA State and Local Energy and Environment Program
(202) 343-9274
Mulholland.Denise@epa.gov

COBRA
Co-Benefits Risk Assessment
Health Impacts Screening and Mapping Tool

State and Local
Energy and Environment Program

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Appendix H: Instructions for Running COBRA Using Batch Files

Batch files can be used to submit emissions data representing multiple years or scenarios, so that the scenarios will run in succession without additional input from the user. This feature enables analysis of multiple years or scenarios in a single modeling step.

Running COBRA using batch files requires that users have some baseline understanding of what batch files are and how they function. Below, we describe how to (1) format emissions files for use in COBRA, (2) write a Windows command to conduct a single COBRA run, and (3) create and run a batch script for multiple COBRA runs.

(1) Formatting emissions files for use in COBRA

COBRA requires that imported baseline emission files be in a specific format. To create properly formatted custom baseline and scenario emissions files, create a CSV file with the headings shown in Exhibit H-1. Each row of the file should correspond to a different source in a different county.

Exhibit H-1. Format of Baseline and Scenario Emissions Files

Column Heading	Description of Column Headings
typeindx[1]	Stack height associated with the emission
sourceindx[2]	Source index, which COBRA uses in its source receptor model
stid	FIPS state ID (e.g., the state FIPS code for Pennsylvania is 42)
cyid	FIPS county ID (e.g., the county FIPS code for Swarthmore, PA is 045)
TIER1[3]	Emissions category to which emissions source corresponds, at tier 1 level
TIER2[3]	Emissions category to which emissions source corresponds, at tier 2 level
TIER3[3]	Emissions category to which emissions source corresponds, at tier 3 level
NO2	NO_x emissions from each source in the baseline
SO2	SO_2 emissions from each source in the baseline
NH3	NH_3 emissions from each source in the baseline
PM25	Primary $PM_{2.5}$ emissions from each source in the baseline
VOC	VOC emissions from each source in the baseline

Notes:

[1] A table of typeindx and name is saved on your computer after installing COBRA in the default location, C:/Program Files/COBRA/input files/data dictionary/typeindx – stack heights.csv.
[2] A table of sourceindx and FIPS is saved on your computer after installing COBRA in the default location, C:/Program Files/COBRA/input files/data dictionary/SOURCEINDX to FIPS crosswalk.csv
[3] A table of tier definitions and tier numbers is saved on your computer after installing COBRA in the default location, C:/Program Files/COBRA/input files/data dictionary/EmissionsTier Definitions.csv

(2) Writing a Windows COBRA command to conduct a single COBRA run

After formatting the baseline emission and scenario emission files, advanced users can run COBRA from the Windows command prompt using the following syntax:

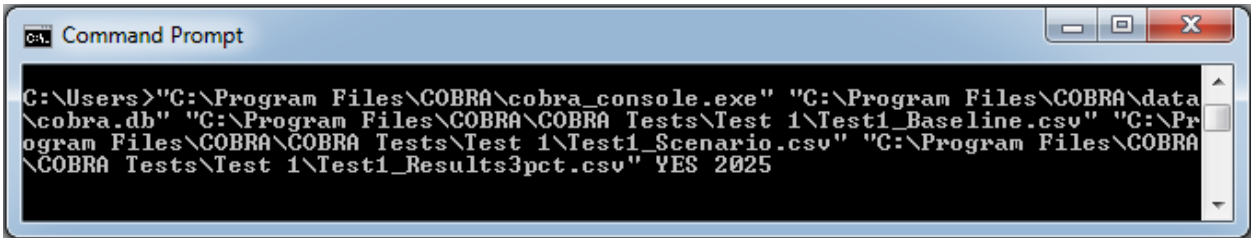
```
"C:\Program Files\COBRA\cobra_console.exe"
"C:\Program Files\COBRA\data\cobra.db" A B C D E
```

where:

- **A** is the file path for the emissions baseline in a CSV file
- **B** is the file path for the emissions control scenario in a CSV file, formatted in the same way as the emissions baseline
- **C** is the file path for where you would like the results CSV to be saved
- **D** is YES or NO, where YES runs COBRA with a 3% discount rate and NO runs COBRA with a 7% discount rate
- **E** is 2017 or 2025, which indicate the year for which population, incidence, and valuation files will be used

Below, we illustrate how one could use this syntax to run COBRA for a single scenario, named Test 1, where **A** = "C:\Program Files\COBRA\cobra_console.exe", **B** = "C:\Program Files\COBRA\COBRA Tests\Test 1\Test1_Scenario.csv", **C** = "C:\Program Files\COBRA\COBRA Tests\Test 1\Test1_Results3pct.csv", and the user wants to run COBRA with a 7% discount rate for year 2025.

```
"C:\Program Files\COBRA\cobra_console.exe"
"C:\Program Files\COBRA\data\cobra.db" "C:\Program
Files\COBRA\COBRA Tests\Test 1\Test1_Baseline.csv"
"C:\Program Files\COBRA\COBRA Tests\Test
1\Test1_Scenario.csv" "C:\Program Files\COBRA\COBRA
Tests\Test 1\Test1_Results3pct.csv" YES 2025
```



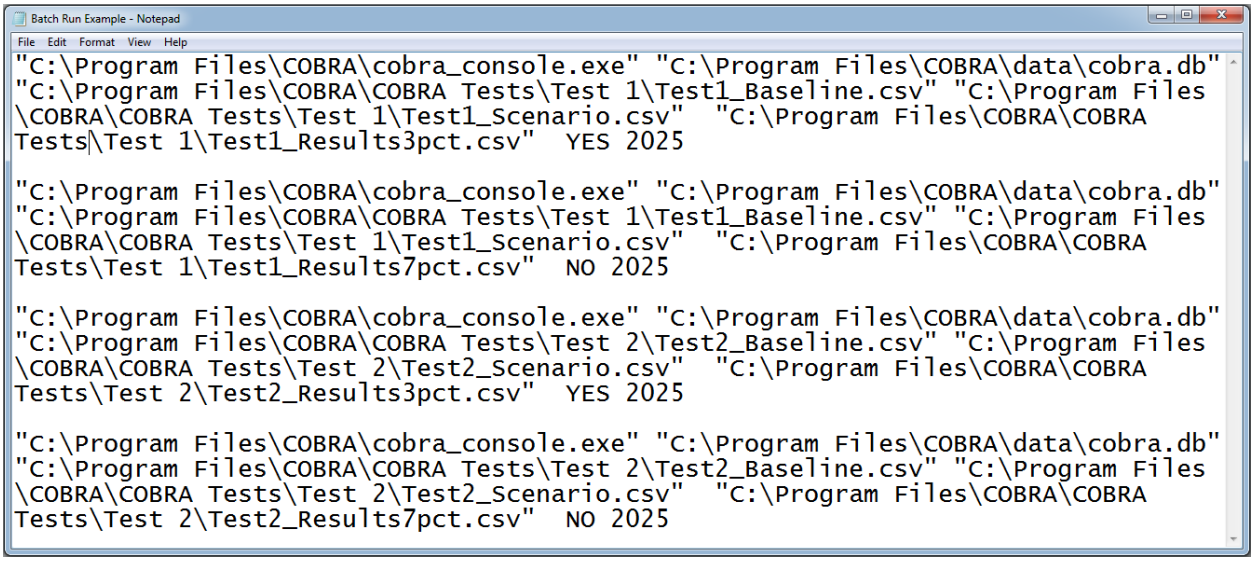
(3) Creating a batch script for multiple COBRA runs

Users can run multiple scenarios in succession without any additional input from the user by creating batch files that contain Windows commands for multiple COBRA runs. Below, we demonstrate how a user could use a batch file to run COBRA four times (1) "Test 1" with a 3% discount rate, (2) "Test 1" with a 7% discount rate, (3) "Test 2" with a 3% discount rate, and (4) "Test 2" with a 7% discount rate, all for year 2025. First, the user would create the properly formatted baseline and scenario emissions files, as described above. For this example, we assume that the following file paths are used:

- `"C:\Program Files\COBRA\COBRA Tests\Test 1\Test1_Baseline.csv"` = file path for the emissions baseline for Test 1

- `"C:\Program Files\COBRA\COBRA Tests\Test 1\Test1_Scenario.csv"` = file path for the emissions scenario for Test 1
- `"C:\Program Files\COBRA\COBRA Tests\Test 1\Test2_Baseline.csv"` = file path for the emissions baseline for Test 2
- `"C:\Program Files\COBRA\COBRA Tests\Test 1\Test2_Scenario.csv"` = file path for the emissions scenario for Test 2

Then, the user would open a simple text editor (e.g. Notepad) and write the series of Windows COBRA commands that describe which baseline emissions, scenario emissions, and discount rate to use for each run, using the syntax described in (2).



Then, the user would save this file a batch file (.bat). To run the batch file, the user would double click the appropriate ".bat" file and the COBRA commands will run automatically in the command prompt.

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