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Public Health Benefits per kWh of Energy Efficiency and Renewable Energy in the United States: A Technical Report

United States Environmental Protection Agency

State and Local Energy and Environment Program

Contents

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Executive Summary

EPA has developed a set of values that help state and local government policymakers and other stakeholders estimate the monetized public health benefits of investments in energy efficiency and renewable energy (EE/RE) using methods consistent with those EPA uses for health benefits analyses at the federal level. It's important to note that EPA is continually reviewing methods and assumptions for quantifying public health benefits. The values presented here and the associated documentation will be updated as appropriate to reflect any future changes in methods or assumptions.

When to use benefits-per-kWh screening values?

Benefits per kilowatt-hour (BPK) values are reasonable approximations of the health benefits of state EE/RE investments that can be used for preliminary analysis when comparing across state and local policy scenarios to indicate direction and relative magnitude.

Examples of analyses where it would be appropriate to use them include:

- Estimating the public health benefits of regional, state, or local-level investments in EE/RE projects, programs, and policies
- Understanding the cost-effectiveness of regional, state, or local-level EE projects, programs, and measures
- Incorporating health benefits in short-term regional, state, or local policy analyses and decision-making

Audience for BPK screening values
Stakeholders interested in approximating the outdoor air quality-related public health benefits from EE/RE, including:

- State and local energy, air quality, or public health agencies
- Public utility commissions
- Energy efficiency and renewable energy project developers
- Industry organization
- Nongovernmental organizations
- Other researchers

When not to use benefits-per-kWh values?

BPK values are not a substitute for sophisticated analysis and should not be used to justify or inform federal regulatory decisions. They are based on data inputs, assumptions, and methods that approximate the dynamics of energy, environment, and health interactions and include uncertainties and limitations, as documented in the technical report.

Benefits-per-kWh screening values

EPA used a peer reviewed methodology and tools to develop a set of screening-level regional estimates of the dollar benefits per kilowatt-hour from four different types of EE/RE initiatives.

- ***Uniform Energy Efficiency*** - Energy efficiency programs, projects, and measures that achieve a constant level of savings over time,
- ***Peak Energy Efficiency*** - Energy efficiency programs, projects, and measures that achieve savings during 12pm-6pm when energy demand is high (i.e. peak),
- ***Solar Energy*** – Programs, projects, and measures that increase the supply of solar energy available (e.g. utility-scale and rooftop solar generation), and
- ***Wind Energy*** – Programs, projects, and measures that increase the supply of wind available (e.g. wind turbines).

Table ES.1. 2017 Benefits-per-kWh Values (cents per kWh, 2017 USD)[1]

Region	Project Type	3% Discount Rate		7% Discount Rate	
		2017 ₵/kWh (low estimate)	2017 ₵/kWh (high estimate)	2017 ₵/kWh (low estimate)	2017 ₵/kWh (high estimate)
California	Uniform EE	0.48	1.08	0.42	0.96
	EE at Peak	0.52	1.17	0.46	1.04
	Solar	0.51	1.15	0.45	1.03
	Wind	0.48	1.09	0.43	0.97
Great Lakes/ Mid-Atlantic	Uniform EE	3.51	7.95	3.14	7.09
	EE at Peak	3.57	8.08	3.19	7.21
	Solar	3.67	8.29	3.27	7.39
	Wind	3.35	7.59	2.99	6.77
Lower Midwest	Uniform EE	2.31	5.23	2.06	4.66
	EE at Peak	2.11	4.77	1.88	4.25
	Solar	2.19	4.96	1.96	4.42
	Wind	2.35	5.32	2.10	4.74
Northeast	Uniform EE	1.65	3.73	1.47	3.33
	EE at Peak	2.24	5.07	2.00	4.52
	Solar	1.94	4.38	1.73	3.91
	Wind	1.58	3.56	1.41	3.18
Pacific Northwest	Uniform EE	1.13	2.55	1.01	2.28
	EE at Peak	1.12	2.54	1.00	2.27
	Solar	1.17	2.64	1.04	2.35
	Wind	1.13	2.55	1.01	2.27
Rocky Mountains	Uniform EE	1.03	2.32	0.92	2.07
	EE at Peak	0.98	2.21	0.87	1.98
	Solar	0.99	2.25	0.89	2.01
	Wind	1.07	2.41	0.95	2.15
Southeast	Uniform EE	1.78	4.02	1.58	3.58
	EE at Peak	1.87	4.24	1.67	3.78
	Solar	1.83	4.15	1.64	3.70
	Wind	1.76	3.98	1.57	3.55
Southwest	Uniform EE	0.71	1.62	0.64	1.44
	EE at Peak	0.70	1.59	0.63	1.42
	Solar	0.73	1.64	0.65	1.46
	Wind	0.77	1.73	0.68	1.54
Texas	Uniform EE	1.58	3.58	1.41	3.19
	EE at Peak	1.39	3.13	1.24	2.80
	Solar	1.42	3.22	1.27	2.87
	Wind	1.63	3.69	1.45	3.29
Upper Midwest	Uniform EE	3.12	7.06	2.78	6.30
	EE at Peak	2.75	6.22	2.45	5.55
	Solar	2.89	6.53	2.58	5.83
	Wind	3.20	7.23	2.85	6.45

[1] In addition to using these regional values, users can also use EPA's AVERT and COBRA tools to develop more specific analyses, such as state- or county-level health benefits estimates. For more information on other more sophisticated options for modeling health benefits for or how to quantify the electricity impacts of energy efficiency and renewable energy, see the EPA report, *Quantifying the Multiple Benefits of Energy Efficiency and Renewable Energy: A Guide for State and Local Governments.*

Understanding the Values

EPA created BPK values using existing tools, including EPA's AVoided Emissions and geneRation Tool (AVERT) and CO-Benefits Risk Assessment (COBRA) Health Impacts Screening and Mapping Tool. BPK values are:

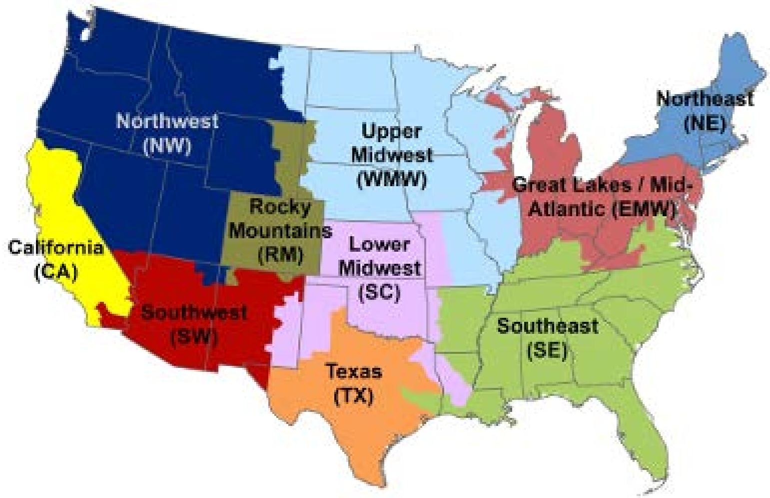

Figure ES.1. AVERT Regions.

- Available for each of the four project types for each of the ten AVERT regions shown in the map below
- Based on 2017 electricity generation data and emissions, population, baseline mortality incidence rate, and income growth projections
- Presented in 2017 dollars and reflecting the use of either a 3% or a 7% discount rate as recommended by EPA's Guidelines for Preparing Economic Analyses (2010)
- Calculated using the same health impact functions EPA uses for regulatory impact analyses, including the calculation of low estimates of mortality using health impact functions that assume people are not very sensitive to changes in $PM_{2.5}$ levels and high estimates of mortality using functions that assume people are more sensitive to changes in $PM_{2.5}$

How to use BPK values?

States and communities interested in having screening-level estimation of outdoor air quality-related health impacts of energy efficiency or renewable energy can multiply the BPK values, presented in Table ES. 1 in cents per kilowatt hour, by the number of kWh saved from EE or generated from RE to estimate potential health benefits from projects in dollars saved. Users should keep in mind there are uncertainties associated with any modeled estimates when interpreting or reporting results.

Introduction

State and local government policymakers have increasingly been asking for the U.S. Environmental Protection Agency's (EPA's) help in understanding the opportunities for using energy efficiency and renewable energy (EE/RE) to reduce air pollution and improve public health. Many recognize that EE/RE projects, programs, and policies can reduce air pollution emissions from the electric power sector either by decreasing demand for electricity generation or by displacing fossil fuel-based generation with zero-emitting sources of generation. They also recognize that these avoided emissions may lead to tangible public health benefits, such as reducing the number of premature deaths, incidences of respiratory and cardiovascular illnesses, and missed work and school days.[2] However, in many cases, state and local decision-makers are not quantifying or fully reflecting the health benefits of existing or planned EE/RE projects, programs, and policies in their decision-making processes. EPA has found that state and local decision-makers may not be fully aware of or confident in the available quantification tools and methods; or they lack the time, resources, or expertise needed to quantify the health benefits.

EPA seeks to address this gap by providing state and local governments and their stakeholders with tools and information to estimate the public health benefits of EE/RE. In particular, EPA has developed screening-level regional estimates of the benefits per kilowatt-hour (kWh) of EE/RE projects, programs, and policies.[3] The goal of these estimates is to create credible and comparable values (i.e., factors) that stakeholders, such as state and local governments, EE/RE project developers, and nongovernmental organizations (NGOs), can use to estimate health benefits of EE/RE projects, programs, and policies. EPA has also sought to ensure that these values are easy to use, and do not require state and local governments or other users to download specific modeling software packages.

This report describes EPA's approach for developing this set of screening-level estimates of the monetized health benefits per kWh that represent the benefits from fossil fuel-based generation reduced or avoided as a result of EE, solar, and wind projects, programs, and policies. The estimates use a 2017 profile of the electricity system to represent the benefits in the near-term of EE/RE projects, programs, and policies that have already been or are about to be implemented. The resulting health benefits-per-kWh (BPK) values can be used by state and local governments, EE/RE project developers, and other stakeholders to develop a more complete picture of the public health benefits of existing or proposed EE/RE projects, programs, and policies. Note that because BPK values provide a screening-level estimate of health benefits of EE/RE, they may not be appropriate for certain analyses, such as federal air quality rulemaking. It's also important to note that EPA is continually reviewing its methods and assumptions for quantifying public health benefits. The health BPK values presented here and the associated documentation will be updated as appropriate to reflect any future changes in EPA methods or assumptions.

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[2] The Health Effects Institute (2018) estimates that in 2016, 105,669 premature deaths in the United States were attributable to air pollution [93,376 due to fine particulate matter ($PM_{2.5}$) and 12,293 due to ozone (O_3)].

[3] These estimates include the contiguous United States, but do not include Alaska and Hawaii. These states are not included in the AVoided Emissions and geneRation Tool (AVERT) used to estimate impacts of EE/RE on air pollution emissions because they do not report emissions data for most of their electric generating units (EGUs) to EPA. Alaska and Hawaii are also not included in the Co-Benefits Risk Assessment (COBRA) Health Impacts Screening and Mapping Tool used to estimate the health impacts of EE/RE because they were not included in the air quality modeling originally used to develop the tool.

Background

Electricity generation in the United States is essential to our economy but it also results in significant emissions of air pollution, depending upon how it is generated. In 2014, the electricity generation sector emitted more than 1 million tons each of nitrogen oxides (NO_x) and sulfur dioxide (SO_2); and more than 170,000 tons of $PM_{2.5}$, which is more than the $PM_{2.5}$ emissions of highway vehicles in that year (EPA 2018). Emissions of these pollutants can result in serious health impacts, including premature mortality, non-fatal heart attacks, asthma exacerbations, and other respiratory diseases. EPA's retrospective analysis of the Clean Air Act (CAA) found that approximately 85 percent of the public health benefits of air quality regulations are due to PM reductions, with the remainder coming from other air pollutants, such as ozone (O_3) (EPA 2011b).

While the U.S. electric power sector has historically been a significant source of air pollution, the sector has undergone rapid change in recent years. Between 2007 and 2016, coal and oil generation sources combined have decreased from just over 50 percent of the U.S. generation resource mix to 31 percent; and renewables, including wind, solar, and geothermal, have increased from just over 1 percent to nearly 7 percent of the resource mix (Table 1). Similarly, electricity savings from energy-efficiency programs were over 180 terawatt hours (TWh) in 2016, an increase of more than 115 percent from 2008 (IEI 2017). All of these changes amount to a cleaner U.S. electric power sector with reduced emissions and health impacts.

Table 1. U.S. Generation Resource Mix, 2007–2016

	Generation Resource Mix (percent)										
Year	**Coal**	**Oil**	**Gas**	**Other Fossil**	**Biomass**	**Hydro**	**Nuclear**	**Wind**	**Solar**	**Geo-Thermal**	**Other/ Unknown**
2007	48.5	1.6	21.7	0.5	1.3	5.8	19.4	0.8	0.0	0.4	0.1
2009	44.5	1.1	23.3	0.3	1.4	6.8	20.2	1.9	0.0	0.4	0.1
2012	37.4	0.7	30.3	0.4	1.4	6.7	18.0	3.4	0.1	0.4	0.1
2014	38.7	0.7	27.5	0.5	1.6	6.2	19.5	4.4	0.4	0.4	0.1
2016	30.4	0.6	33.8	0.3	1.7	6.4	19.8	5.6	0.9	0.4	0.1

Source: EPA eGRID.

In order to help state and local governments quantify the health benefits of EE/RE, EPA first needed to understand the current state of the scientific literature to determine if there are best practices or factors that states could apply. EPA commissioned a literature review that examined more than 60 studies for BPK values in order to better understand current methods and health benefits of EE/RE projects, programs, and policies (EPA 2017). Through the literature review, EPA found that the results varied depending on the approach used, the benefits included, and the geographic focus of the analysis. Therefore, the resulting sets of BPK values identified in the literature review were not easily comparable to one another.

Lawrence Berkley National Laboratory (LBL), for example, published several studies examining both the prospective and retrospective health benefits from wind, solar, and renewable portfolio standard (RPS) programs across the United States (Table 2). The benefits reported by each study are an average value of health benefits calculated using multiple different air quality and health impact models, including the Air Pollution Emission Experiments and Policy Analysis Model

(AP2), EPA's benefit-per-ton methodology, EPA's CO-Benefits Risk Assessment (COBRA) Health Impacts Screening and Mapping Tool, and the Estimating Air Pollution Social Impact Using Regression (EASIUR) model. Overall, these studies provide a range nationally between 2.6¢/kWh and 10.1¢/kWh for recent years, and between 0.4¢/kWh and 8.2¢/kWh when looking prospectively. Other studies included in the literature review generated a different range of results that were not directly comparable to the LBL estimates, typically because they used a variety of models or included additional benefits. For example, some of the models used in studies identified in the literature review include non-health, welfare benefits, such as avoiding damages from decreased timber and agricultural yields, reduced visibility, accelerated depreciation of materials, and reductions in recreation services; results from these studies may be higher than the values calculated using models that focus solely on health benefits.

Table 2. Public Health Benefits from wind, solar, and RPS program across the US

Program Evaluated	Benefit-per-kWh (¢/kWh)	Source
2013 RPS programs	2.6¢/kWh - 10.1¢/kWh	Barbose et al. 2016
2015 Wind energy	7.3/¢kWh	Millstein et al. 2017
2015 Solar energy	4¢/kWh	Millstein et al. 2017
2015-2050 RPS Programs	2.7¢/kWh - 8.2¢/kWh	Mai et al. 2016
2050 Wind energy	0.4¢/kWh - 2.2¢/kWh	Wiser et al. 2016a
2050 Solar energy	0.7¢/kWh - 2.6¢/kWh	Wiser et al. 2016b

The literature review also identified two key gaps across all available estimates. While several studies estimated the benefits per kWh in specific regions, particularly the Northeast and California, there is no comprehensive set of monetized health benefits per kWh from EE/RE for all U.S. regions. The national numbers provided by LBL do not appropriately represent regional differences in the specific composition of electricity generation throughout the United States and therefore do not account for regional differences in emissions. Additionally, the values from the literature are not methodologically consistent, and can therefore not be compared with confidence. These gaps limit practitioners' abilities to include health benefits in the assessments of EE/RE projects or programs, or policy costs and benefits.

This study fills these gaps identified in the literature review by quantifying and presenting easy-to-use health BPK values for a range of EE/RE types that are comparable with each other and cover all regions in the United States. These BPK values are calculated in a similar fashion to EPA's existing estimates of monetized public health benefits-per-ton of emissions reductions in that both sets of estimates take health benefits and divide them by an amount of emissions or generation reduction (Fann et al. 2009).[4]

[4] EPA has used the benefits-per-ton estimates in multiple regulatory impact assessments for air quality regulations, such as the Mercury and Air Toxics Standards; the New Source Performance Standards for Petroleum Refineries; and the National Emission Standards for Hazardous Air Pollutants for Industrial, Commercial, and Institutional Boilers and Process Heaters. For more information, see https://www.epa.gov/economic-and-cost-analysis-air-pollution-regulations/regulatory-impact-analyses-air-pollution.

In general, the literature review examined common approaches to estimating BPK values and identified a series of best practices for estimating these values in the United States. The best practices include:

1. Establish a set of public health BPK values for interventions in specific regions, rather than a single national value, to account for regional differences in generation and air pollution control technologies.
2. Establish separate BPK values for different types of EE/RE projects, programs, and policies, such as wind, solar, uniform EE, and EE at peak, to account for how different technologies impact the load (i.e. demand) curve.[5]
3. Establish BPK values for interventions of varying capacity to capture the benefits stemming from EE/RE interventions that can displace power from baseload, intermediate load, and peaking units.
4. Account for changes in primary and secondary $PM_{2.5}$ emissions and, whenever feasible, changes in O_3 concentrations in health BPK values, to capture the majority of health impacts from outdoor air pollution.[6]
5. Use emissions, population, and income datasets from the same year to maintain internal consistency.

The BPK values included in this report are estimated using a method informed by these best practices. EPA also sought input on the methods for this analysis from outside experts in energy modeling, health benefits estimation, electricity system operations, and EE/RE policy and deployment. The remainder of this report describes the methods used to estimate screening-level BPK values and results of the analysis. The report also contains technical appendices with more information on the tools and models used in the analysis, as well as the results of sensitivity analyses performed to address uncertainty in the estimates.

Methods

In this section, EPA provides a general overview of the approach used to estimate the near-term benefits per kWh of EE/RE,[7] and then discusses in more detail the electricity, emissions, and health impact modeling steps used to develop the BPK values.

Overview of Approach

EPA's approach for estimating the screening-level health benefits per kWh of EE/RE projects, programs, and policies involves a six-step process:

1. Estimate changes in fossil-based electricity generation due to representative EE/RE projects, programs, and policies.
2. Estimate changes in air pollution emissions (NOx, SO_2, and $PM_{2.5}$) due to changes in fossil-based generation.

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[5] See the Energy-Efficiency Scenarios section on page 6 of this report for definitions of uniform EE and EE at peak.

[6] EPA's retrospective analysis of the CAA found that approximately 85 percent of the public health benefits of air quality regulations are due to PM reductions, rather than O_3 (EPA 2011b).

[7] The "near term" is defined as approximately the next five years, which is discussed in more detail in the Limitations section on page 15.

3. Estimate changes in ambient concentrations of air pollution due to changes in emissions of primary $PM_{2.5}$ and precursors of secondary $PM_{2.5}$.[8]
4. Estimate changes in public health impacts due to changes in ambient concentrations of $PM_{2.5}$.
5. Estimate the monetary value of changes in public health impacts.
6. Divide the monetized public health benefits by the change in generation to determine the health benefits per kWh (¢/kWh).

This approach follows well-established methodologies for estimating the magnitude and economic value of public health benefits of air pollution emissions reductions, which have been documented in the literature (e.g., Dockins et al. 2004, Fann et al. 2012) and used in recent EPA Regulatory Impact Analyses (RIAs). Based on these established methodologies, EPA chose not to include reductions of carbon dioxide (CO_2) in this analysis because it is generally only included in studies that assess climate and welfare impacts in addition to public health impacts.

In order to quantify public health benefits in the near-term, EPA developed a set of values for the year 2017. To carry out the approach for these estimates, EPA used two peer-reviewed Agency tools, the AVoided Emissions and geneRation Tool (AVERT)[9] and the COBRA tool.[10] Figure 1 depicts the approach outlined above as it relates to the tools used in this analysis. These tools are described further in *Appendix A: AVoided Emissions and geneRation Tool* and *Appendix B: Co-Benefits Risk Assessment (COBRA) Health Impacts Screening and Mapping Tool*.

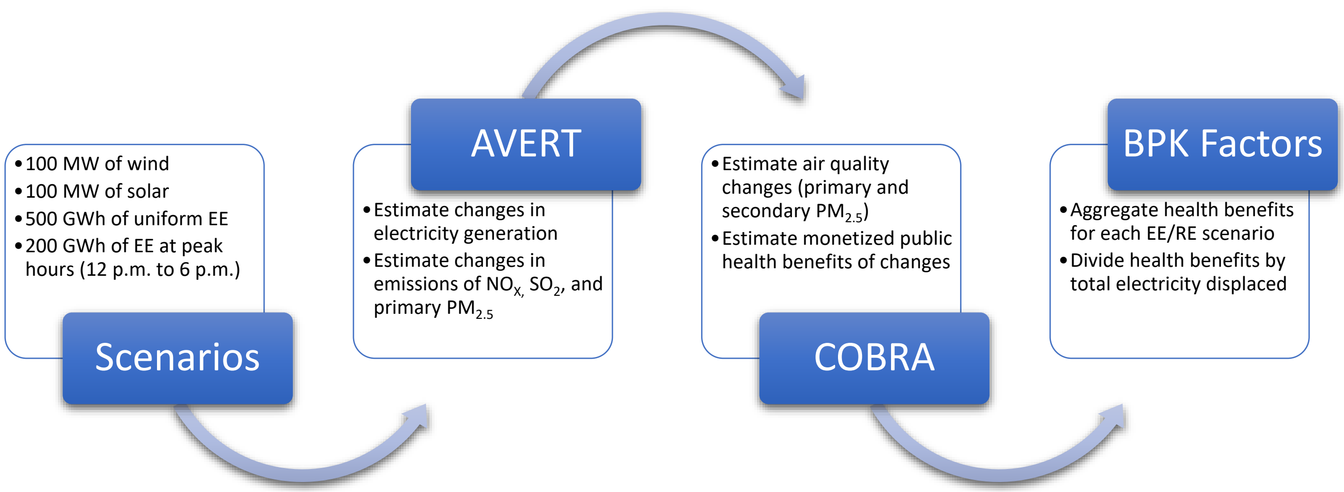

Figure 1. BPK Approach.

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[8] Primary $PM_{2.5}$ refers to the direct emissions of PM from EGUs. Secondary $PM_{2.5}$ is created as emissions of SO_2 and NO_x [and other pollutants such as ammonia and volatile organic compounds (VOCs)] undergo chemical reactions in the atmosphere.

[9] EPA AVERT; see https://www.epa.gov/statelocalenergy/avoided-emissions-and-generation-tool-avert.

[10] EPA COBRA Health Impacts Screening and Mapping Tool; see https://www.epa.gov/statelocalenergy/co-benefits-risk-assessment-cobra-screening-model.

Modeling Scenarios Development

EPA considered multiple scenarios to estimate changes in electricity generation and emissions due to EE/RE projects, programs, and policies. During the scenario development process, EPA sought input from technical experts in EE/RE modeling and analysis, and refined the scenarios based on their comments. For a description of how these scenarios were used to estimate changes in electricity generation and emissions, see the *Electricity and Emissions Modeling* section on page 14, as well as *Appendix A: AVoided Emissions and geneRation Tool (AVERT)*.

Renewable Energy Scenarios

For RE, EPA chose to model separate scenarios for wind and solar projects. These projects have different impacts on the timing of generation (i.e., solar only generates during the daytime while wind can generate during more hours of the day) and may therefore have different impacts on emissions reductions in each region. EPA modeled both the wind and solar in AVERT as 100-megawatt (MW) projects. The assumptions EPA made in choosing this project size are discussed in more detail in the *Project, Program, and Policy Size Assumptions* section (page 13).

EPA considered modeling several other RE scenarios before deciding to model 100-MW projects. These scenarios included:

- A mix of wind and solar to estimate a portfolio of RE projects. However, EPA decided that to estimate the benefits of a single mix of wind and solar would have limited value, given than most states and regions have different mixes of wind and solar generation. Therefore, EPA decided to provide separate estimates of BPK values for wind and solar generation.
- Separate scenarios for utility-scale and rooftop solar generation, as AVERT allows the user to model those technologies separately. However, the supply curves for these project types are very similar and result in similar emissions reductions per kWh. Therefore, for simplicity, EPA is reporting a single value for solar projects, which is based on a utility-scale solar project modeled in AVERT.

Stakeholders can use the individual wind and solar values to evaluate the benefits of a mix of wind and solar generation in a particular region. The impacts of EE/RE projects, programs, and policies are additive as long as the additional capacity does not exceed 15 percent of fossil generation in any given hour in a region. This cap on capacity is a limit set by EPA and is due to the fact that AVERT is a historical dispatch model that is limited in its ability to estimate emissions reductions for projects, programs, or policies that may significantly alter the generation mix in a region. Capacity added beyond this 15 percent cap may have a different impact on emissions that is not captured by the model. For more information on project size limits when using AVERT, see the *Project, Program, and Policy Size Assumptions* (page 10), *Uncertainty* (page 14), and *Limitations* (page 16) sections in this report.

Energy-Efficiency Scenarios

EPA developed two scenarios for EE projects, programs, and policies: uniform EE and EE at peak. EPA modeled uniform EE in AVERT as a 500-gigawatt hour (GWh) reduction in electricity demand, distributed evenly throughout all hours of the year. EPA modeled EE at peak as a 200-GWh reduction distributed evenly (but exclusively) during the limited hours of 12 p.m.

to 6 p.m. on weekdays. The assumptions EPA made in choosing this project, program, and policy size are discussed in more detail in the *Project, Program, and Policy Size Assumptions* section on page 13.

Uniform EE is based on a constant reduction in electricity demand applied evenly to all hours of the year. This assumes that an EE intervention would reduce demand for electricity to the same degree during all hours of the day and for all seasons. For example, installing energy-efficient exit signs (which operate 24 hours a day, seven days a week) will result in constant or uniform reductions, because the signs lower demand during all hours of the year. Alternatively, a mixed portfolio of EE strategies that, taken together, saves electricity in a relatively uniform pattern throughout the year can be viewed as a uniform EE intervention.[11]

The EE at peak scenario assumes that EE reductions occur only during certain times of the day when demand is highest (often called "peak hours"). In states with warmer climates this is often the afternoon hours in the summer, while colder states have peak hours during winter mornings; some states have both morning and afternoon peak hours. Air conditioners are an example of a technology that largely impacts the load curve during summer peak hours. Air-conditioning (A/C) units often consume more electricity during peak times when people return home from work or school. Installing an energy-efficient air conditioner is, therefore, an example of a measure that largely affects generation during peak hours.

The types of EGUs that typically operate on the margin during peak hours often differ from those that operate on the margin at other times of the day.[12] Peaking units are generally natural gas units that can ramp up and down quickly compared to baseload coal or nuclear units that typically operate 24 hours a day. Because emissions from these types of power plants can vary significantly, the reduction in emissions will likely also vary for different types of EE interventions.[13] Note that interventions that result in load reductions during the peak hours may also result in load reductions during off-peak hours. For example, an energy-efficient A/C unit will result in decreased demand in all hours in which it is in use, even though the largest reductions will occur during peak hours. Nevertheless, because these types of EE interventions result in significant load reductions during peak hours, it is useful to examine the difference in benefits provided by load reductions during peak hours compared to those from a more uniform load reduction.

In order to model the EE at peak scenario, it is necessary to select a window of time along the load curve as representative of system peak. However, there is currently no universally agreed-

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[11] An example of how a portfolio of EE programs can save electricity relatively uniformly throughout the day is demonstrated in the graphic on page 3 of the Southern California Edison Preferred Resources Pilot Annual Update for 2018: https://www.sce.com/wps/wcm/connect/e134c4a9-aff0-4ddf-a8a0-cf9d5a0e3304/2017_PRPAnnualReport.pdf?MOD=AJPERES.

[12] EPA defines EGUs on the margin as "the last units expected to be dispatched, which are most likely to be displaced by energy efficiency or renewable energy." For more information, see chapter 3 of the EPA report, *Quantifying the Multiple Benefits of Energy Efficiency and Renewable Energy: A Guide for State and Local Governments*: https://www.epa.gov/statelocalenergy/quantifying-multiple-benefits-energy-efficiency-and-renewable-energy-guide-state

[13] For example, natural gas single cycle turbines are well-suited to serve peak load because of their quick start-up capability, but these units generally have higher NO_x emissions than natural gas combined cycle plants, which are more efficient and typically serve intermediate or even baseload demand.

upon definition of peak hours. When electric utilities are managing the operations of existing EGUs, they often define the peak period based on the hour of day. Utilities know that demand tends to increase in the afternoons in the summer and early mornings/late evenings in the winter and adjust their operations accordingly. EPA compared various definitions of the peak period to determine which definition to use for estimating the EE at peak BPK values.

EPA reviewed definitions of peak hours from several utilities in different parts of the country (Figure 2). The definitions of peak hours differed slightly among the utilities (e.g., some are from 2 p.m. to 6 p.m., some include morning hours, some differ by season). EPA conducted a sensitivity analysis by modeling the same generation reduction for each utility's definition of peak, including seasonal variations. For example, Duke Energy defines the peak period in the winter from 6 a.m. to 9 a.m. and in the summer from 1 p.m. to 6 p.m.; while Pacific Gas and Electric (PG&E) defines the peak period only during 1 p.m. to 7 p.m. in the summer but does not include a peak period in the winter. The sensitivity analysis involved running scenarios for all 10 AVERT regions using the definitions of the peak period, discussed in more detail in *Appendix C: Sensitivity Analyses on Project, Program, or Policy Size and Peak Energy-Efficiency Definition*. This analysis found that the differences in the definition of peak hours do not result in large differences in emissions reductions within each region when modeled in AVERT. Therefore, EPA chose to use the general definition of 12 p.m. to 6 p.m. on weekdays for peak hours, as this scenario also generated similar emissions reductions compared to the other definitions in all regions. The results of the sensitivity analysis on the definition of peak hours are discussed in more detail in *Appendix C: Sensitivity Analyses on Project, Program, or Policy Size and Peak Energy-Efficiency Definition*.

In addition to defining the peak period based on the hour of day, it can also be defined as the top hours of demand during the year. Utilities generally use this approach to determine whether and when to build new capacity, because they must ensure they have enough capacity to meet even the highest days of demand (e.g., the peak period could be based on the top 200 hours of demand). In most regions, these high periods of demand are concentrated in the hottest summer afternoons. By contrast, defining the peak period as 12 p.m. to 6 p.m. on weekdays includes more than 1,500 hours during the year. EPA conducted a sensitivity analysis to compare these definitions of the peak period by estimating emissions reductions in all 10 AVERT regions in 2017 using both a "top 200 hours approach" and an "hour of day approach" to define the peak period. The results of this sensitivity analysis show large differences in the emissions rate in some regions. The full results of this sensitivity analysis are discussed in *Appendix C: Sensitivity Analyses on Project, Program, or Policy Size and Peak Energy-Efficiency Definition*.

After consultation with energy-sector experts, EPA ultimately determined that the hour-of-day approach is more relevant for this analysis. Only very-specific technological interventions or EE programs or policies would coincide with just the top 200 hours of demand, and the use of this definition would, therefore, not accurately capture all the benefits from broader programs or policies.

The two definitions of the peak period described above are used for different purposes by electric utilities—the hour-of-day approach is used to manage existing capacity and the top-hours-of-demand approach is used to plan for additional capacity. EPA asserts that most independent developers, nonprofits, and state/local users of these BPK values will be more interested in capturing the impacts of an EE project, program, or policy on the existing or projected fleet of EGUs, rather than planning for additional capacity, and therefore the Agency reports values using the hour-of-day approach as the primary BPK values for EE at peak in this analysis. However, if a utility is planning to use BPK values to estimate the health benefits of an EE project, program, or policy in order to avoid investing in new generation, transmission, and distribution, then the top-hours-of-demand approach may be more appropriate. BPK values calculated using a top 200 hours approach are shown in *Appendix D: Top 200 Hours of Demand Benefit-per-kWh Results*.

Nevertheless, this definition of the peak period should inform how BPK values are used. If an EE project, program, or policy results in generation reductions only during the top 200 hours of demand, then it may have a different emissions profile and, therefore, different health benefits than the type of EE at peak modeled here. Analysts have the option of developing their own custom BPK estimates using AVERT and COBRA if the estimates EPA provides do not fit their unique circumstances.

Project, Program, and Policy Size Assumptions

RE/EE Scenarios

- 100 MW of added wind capacity
- 100 MW of added solar capacity
- 500 GWh of uniform EE
- 200 GWh of EE during peak hours (12 p.m. to 6 p.m., weekdays)

EPA modeled the RE projects assuming a project, project, or policy size of 100 MW and modeled the EE projects assuming generation reductions of 500 GWh for uniform EE scenarios and 200 GWh for EE during peak hours. It is possible that larger EE/RE projects could displace a different set of EGUs, resulting in disproportionately larger (or smaller) emissions reductions and health benefits. To determine whether the project size would have a large effect on BPK estimates, EPA conducted a sensitivity analysis by running AVERT with five different project sizes, ranging from 100 MW to 2,000 MW for RE and 100 GWh to 2,000 GWh for EE. The results from each AVERT run were entered into COBRA to estimate the health benefits. The results from both AVERT and COBRA demonstrated strong linear relationships (R^2 = 0.9996–1.0). This means that the BPK values were nearly constant across all the project sizes tested in the sensitivity analysis. As a result, the results presented here used a single assumption about project size for each technology type. The full results for this sensitivity analysis are shown in *Appendix C: Sensitivity Analyses on Project, Program, or Policy Size and Peak Energy-Efficiency Definition*.

EPA chose the 100 MW and 200 and 500 GWh sizes for RE and EE projects, programs, and policies respectively because they are large enough to generate significant emissions reductions but small enough that they do not displace more than 15 percent of fossil generation in any given hour. AVERT is a historical dispatch model that is limited in its ability to estimate emissions reductions for projects, programs, or policies that may significantly alter the generation mix in a region. EPA recommends that users avoid modeling scenarios in which the EE/RE project, program, or policy would reduce more than 15 percent of fossil-fuel generation in any given hour.[14] The size an individual project, program, or policy can range widely before hitting that

[14] In general, EE/RE impacts greater than 15 percent of regional fossil-load could influence the historical dispatch patterns that AVERT's statistical module is based upon. AVERT should not be used to change dispatch based on future economic or regulatory conditions, such as expected fuel prices, emissions prices, or specific emissions limits.

limit, depending on the amount of fossil generation in each region. For example, in the California region, a 400-MW solar project would exceed that limit. In the Southeast, however, a solar project could be as large as 14,000 MW before hitting the 15-percent threshold. Table 3 lists the 15-percent thresholds in all regions for the scenarios included in this report. Furthermore, EPA also recommends users avoid estimating emissions reductions for projects less than roughly 1 MW because the resulting emissions reductions estimated by the model are too small to be distinguished from the underlying variation in the baseline data.

Table 3. AVERT 15-percent Threshold of Fossil-Fuel Generation in 2017

Region	Wind (MW)	Utility Solar (MW)	Uniform EE (GWh)	EE at Peak (GWh)
California	469	309	1,825	340
Great Lakes/Mid-Atlantic	6,223	9,568	36,582	9,733
Lower Midwest	1,388	1,999	8,341	2,318
Northeast	1,235	1,429	4,386	1,660
Northwest	1,191	827	4,275	843
Rocky Mountains	610	604	3,461	868
Southeast	19,465	14,496	55,084	15,111
Southwest	1,437	1,177	7,504	1,602
Texas	2,425	3,705	13,025	4,240
Upper Midwest	2,106	3,467	14,562	3,845

Electricity and Emissions Modeling

To estimate the changes in electricity generation and associated changes in emissions due to EE/RE projects, programs, and policies (steps 1 and 2 in the overall approach), EPA used AVERT. AVERT uses hourly emissions and generation data reported to EPA by EGUs to determine the air pollution emissions per kWh from each generating unit, as well as the probability that a given unit will be operating during a given hour.[15] AVERT uses this information to estimate which fossil-fired units will likely be affected by EE/RE projects, programs, and policies; and the amount of emissions displaced or avoided. The results from AVERT are the estimated emissions reductions of NO_x, SO_2, and $PM_{2.5}$ from the modeled EE or RE project, program, or policy. The results from AVERT are presented at the county, state, and regional levels.

The 2017 estimates in this analysis were developed using actual emissions and generation of fossil-fired EGUs in 2017, which are built into the latest version of AVERT. The assumptions about how AVERT uses historical data to estimate emissions reductions are discussed in more detail in *Appendix A: AVoided Emissions and geneRation Tool (AVERT).*

EPA developed separate estimates for each of the 10 AVERT regions (Figure 2) in order to take into account regional differences in generation power plant fuel mixes and air pollution control

[15] Facilities are required under 40 CFR Part 75 to report information on emissions, heat rate, and generation to EPA's Clean Air Market Division (CAMD) for EGUs 25 MW or larger.

technologies.[16] These regions are based on the Emissions & Generation Resource Integrated Database (eGRID) subregions and NERC regions. EPA modeled each scenario, outlined above, in each region in 2017; 40 estimates of emissions reductions were developed.

Air Quality and Health Impact Modeling

Once EPA developed estimates of emissions reductions by applying AVERT for all scenarios, EPA used the COBRA Health Impacts Screening and Mapping Tool to complete steps 3, 4, and 5 of the approach—estimating changes in ambient air quality, impacts on public health, and monetized health benefits from emissions reductions, respectively.

COBRA uses a reduced-form air quality model called the Phase II Source-Receptor (S-R) Matrix to develop screening-level estimates of how changes in emissions at source counties will affect ambient $PM_{2.5}$ concentrations in receptor counties. The S-R Matrix was developed using multiple runs from the Climatological Regional Dispersion Model (CRDM), a more sophisticated air quality model, and it is intended as a screening-level tool, which can be run more quickly than the full model. COBRA accounts for both primary (i.e., directly emitted) $PM_{2.5}$ emissions and the formation of secondary $PM_{2.5}$ in the atmosphere from the reaction of SO_2 and NO_x with ammonia (NH_3).

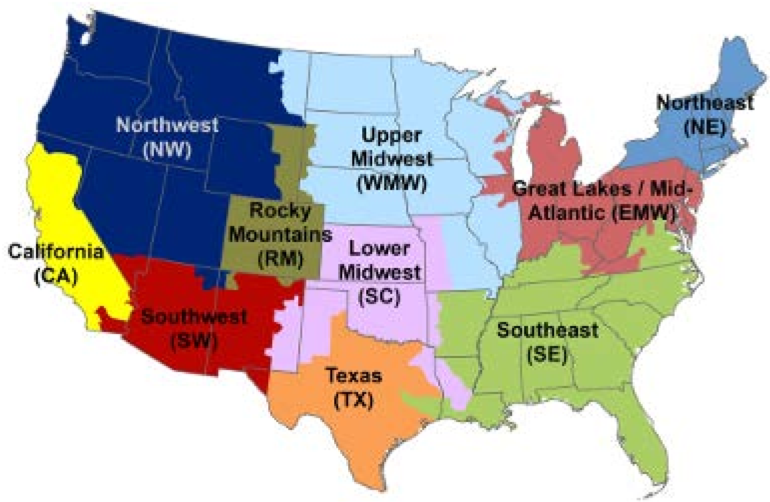

Figure 2. AVERT Regions.

COBRA also uses concentration-response (C-R) functions from the epidemiological literature to determine how changes in ambient $PM_{2.5}$ concentrations will impact health outcomes, such as premature mortality, non-fatal heart attacks, asthma exacerbations, and other respiratory symptoms. Finally, COBRA uses established valuation functions from the economic literature to estimate the monetary value of each health outcome. C-R and valuation functions used in COBRA are consistent with those used in EPA's Environmental Benefits Mapping and Analysis Program (BenMAP) and in RIAs conducted by the Agency. COBRA assumes that National Ambient Air Quality Standards (NAAQS) are met in all states and counties, and, therefore, estimates incremental health benefits from reduced exposure below the standards.[17] The result from COBRA is the estimated avoided public health outcomes from emissions reductions and the monetary value of those avoided public health outcomes. The results from COBRA are presented at the county level. For more information on

[16] Note that AVERT implicitly accounts for control technologies because it uses unit-level emissions data to estimate emissions from electricity generation.

[17] The 2012 NAAQS are not set at a zero-risk level, but a level that protects public health; both EPA and the Integrated Science Assessment for Particulate Matter have acknowledged that health risks remain below the level of the standard. Therefore, emissions reductions below the standard will still result in health benefits.

the COBRA tool, see *Appendix B: Co-Benefits Risk Assessment (COBRA) Health Impacts Screening and Mapping Tool*; for detailed information on the C-R functions used in COBRA, see *Appendix E: Health Impact Functions*; and for detailed information on the valuation functions used in COBRA, see *Appendix F: Health Benefits Valuation*.

For this analysis, EPA used the 2017 baseline emissions inventory housed in COBRA v3.0. Given that AVERT uses 2017 data, EPA did not make any changes to the baseline data in either AVERT or COBRA.

County-level emissions reductions from each AVERT run were entered into the COBRA tool. This tool allows users to select from multiple emissions tiers, or categories of emissions sources, in order to more accurately determine the health impacts due to reductions in emissions from that category. COBRA takes into account the height of the smokestacks of the emissions sources in each emissions tier, which impacts the modeled transport of pollution.[18] EPA entered emissions reductions using the tier for Fuel Combustion from Electric Utilities.

COBRA also gives users the ability to choose between a 3 percent or 7 percent discount rate that will be used in the economic analyses completed by the model.[19] Following the Agency's *Guidelines for Preparing Economic Analyses* (EPA 2010), EPA ran scenarios using both the 3 percent and 7 percent discount rates. This allowed EPA to evaluate the effect of the discount rate on monetized health benefits of EE/RE projects, programs, and policies.

For each discount rate, COBRA reports a low and high estimate of the monetary value of the health benefits impacts, based on the use of different C-R functions (e.g., different mortality functions). Specifically, the low and high estimates are derived using two sets of assumptions from the literature about the sensitivity of adult mortality and non-fatal heart attacks to changes in ambient $PM_{2.5}$ levels. EPA used these low and high estimates for both the 3 percent and 7 percent discount rates to report the total health benefits of all scenarios as a range.

Developing the Health Benefits-per-kWh Estimates

AVERT presents results at the county and regional levels, whereas COBRA only presents results at the county level. EPA aggregated the total county-level results from each COBRA scenario and developed the monetized health BPK estimates (¢/kWh) for each region and each scenario by dividing the total monetized health benefits ($) from COBRA by the total regional-level reduction in generation (kWh) from AVERT.

While the inputs to COBRA are based on emissions reductions occurring in each AVERT region, the COBRA results also include health benefits that occur outside the region(s) where modeled emissions reductions occur. This is because COBRA accounts for the transport of pollution to air sheds located downwind of an emissions source. For example, emissions reductions from EGUs in the Great Lakes/Mid-Atlantic region will likely result in health benefits within that region and also in neighboring regions downwind of the power plant smokestacks,

[18] For example, the highway vehicles tier assumes all emissions are at the ground level; while the electric utilities tier assumes emissions are from taller smoke stacks, which result in the transport of pollution across farther distances.

[19] COBRA accounts for most health impacts during only the year of the analysis (i.e., 2017). However, the C-R functions for premature mortality and nonfatal heart attacks are based on a 20-year increase in incidence. Therefore, the benefits from avoiding these specific health impacts are discounted to determine their present value.

such as the Northeast region, due to the interstate transport of air pollution. In the BPK calculations, EPA aggregated the total health benefits calculated by COBRA for each scenario to account for all of the health benefits that occur both within the AVERT region where the emissions reductions occur, and in other regions that also experience health benefits from those emissions reductions. This approach is consistent with other EPA estimates of monetized public health benefits per ton of emissions reductions (Fann et al. 2009).

Screening-level health benefits per kWh of each scenario are estimated using the following equation:

$$BPK_{t,r} = \frac{HealthBenefits_{t,US}}{GenerationChange_{t,r}}$$

Where:

$BPK_{t,r}$	=	Monetized public health benefits per kilowatt-hour (¢/kWh) for each EE/RE technology type (*t*) and AVERT region (*r*)
$HealthBenefits_{t,US}$	=	Aggregated monetized public health benefits from emissions reductions for each type of EE/RE technology type (*t*) for the contiguous United States (US)
$GenerationChange_{t,r}$	=	Change in electricity generation for each EE/RE technology type (*t*) and AVERT region (*r*).

Uncertainty

As described above, EPA calculated the BPK values using a suite of models that are each affected by various sources of uncertainty. While data limitations prevent EPA from quantifying these uncertainties, the Agency can qualitatively characterize the sources and magnitude of the uncertainties from electricity and emissions modeling, and air quality and health impact modeling. EPA discusses here these sources of uncertainty, as well as steps taken within the models and by EPA to mitigate this uncertainty. This discussion also includes an assessment of whether each source of uncertainty leads to an overestimate or underestimate of the BPK values, where possible. In addition, this section also includes a discussion of the uncertainty over the length of time into the future that these values can be used for analysis. EPA does not attempt to quantify the uncertainty in the BPK values (e.g., by calculating a confidence interval around each estimate). Readers interested in reviewing a comprehensive quantitative analysis of the uncertainty of the impacts of PM on public health should consult the RIA for the PM NAAQS (EPA 2013).

Uncertainty in Electricity and Emissions Modeling

EPA identified three main sources of uncertainty stemming from estimating EE/RE-related emissions reductions using AVERT. Estimates in AVERT are calculated using a single assumption about project size. These estimates could, therefore, be sensitive to project size, and under- or overestimate reductions if applied to larger or smaller projects. As discussed in the *Project, Program, and Policy Size Assumptions* section above on page 13, to address this uncertainty, EPA conducted sensitivity analyses varying the project size from 100 MW to 2,000 MW of added capacity for wind and utility solar, and varying EE definitions. This analysis is discussed in detail in *Appendix C: Sensitivity Analyses on Project, Program, or Policy Size and Peak Energy-Efficiency Definition*; and shows that changes in project size do not have a large impact on the resulting BPK values.

Uncertainties also exist in the cohort of marginal units AVERT simulates when there are changes in demand or RE generation within an AVERT region. The core emissions, heat rate, and generation information AVERT uses is based on historical datasets that utilities report to EPA's Clean Air Market Division (CAMD) for EGUs 25 MW or larger. AVERT's statistical module uses probability distributions of how EGUs operated historically in every hour of a base year to determine which cohort of EGUs are on the margin. Refer to *Appendix A* for more details on AVERT's operations.[20] Additionally, AVERT does not report results for cases that are not above the level of reportable significance. This prevents AVERT from falsely reporting emissions outcomes of very small EE/RE project, program, or policy impacts. For example, AVERT does not report any emissions impacts less than 10 lbs. of a criteria air pollutant and does not report any results less than 10 tons of CO_2. Furthermore, there is some uncertainty in how the regions are defined. Although AVERT regions are based on eGRID subregions and NERC regions, the electricity grid is interconnected and there are transfers of electricity across regions. AVERT does not currently account for these transfers since this could lead to isolating impacts within a region that may affect power plants outside of the region. This could result in either an overestimate or an underestimate of the emissions impacts, depending on which regions are transferring electricity.

Additionally, AVERT only includes fossil fuel-generating units. However, some states, such as California, experience a curtailment of generation from renewable sources when there is an oversupply of electricity generation during certain hours of the year. Curtailment is defined as "a reduction in the output of a generator from what it could otherwise produce given available resources, typically on an involuntary basis" (Bird et al. 2014, p. 1). By assuming that only fossil sources are displaced and not accounting for the fact that some renewable sources could be displaced, the BPK results could overestimate the health benefits of EE/RE. For more information on this issue, see the *Limitations* section on page 19.

Uncertainty in Air Quality and Health Impact Modeling

EPA identified sources of uncertainty from using COBRA to model changes in air quality, health impacts, and the value of those impacts. The largest source of uncertainty in the COBRA tool is the S-R Matrix, which consists of fixed transfer coefficients that reflect the relationship between emissions at source counties and ambient air pollution concentrations at receptor locations. Even though the S-R Matrix was developed as a screening-level tool using a more advanced model (CDRM), it still represents a simplification of the transport of air pollution, and it is less sophisticated than a photochemical grid model, such as the Community Multiscale Air Quality Modeling System (CMAQ), which would quantify the non-linear chemistry governing the formation of $PM_{2.5}$ in the atmosphere. Due to the uncertainty surrounding the S-R Matrix, COBRA is considered a screening-level tool; for more detailed estimates of air quality changes,

[20] For more information on AVERT's statistical module, refer to Appendix D in the AVERT User Manual: https://www.epa.gov/statelocalenergy/avert-user-manual.

more sophisticated models should be used.[21] However, COBRA has been used extensively in the peer-reviewed literature and has been compared favorably to the estimates from CALPUFF, a more sophisticated air quality model (Levy et al. 2003). It is not clear whether the uncertainty with the S-R Matrix leads to an overestimate or underestimate of the BPK values.

The C-R and valuation functions used in COBRA to estimate and monetize public health impacts are another source of uncertainty. The functions used in COBRA do not represent the complete body of epidemiological literature but are consistent with those used in recent EPA regulatory analyses. Additionally, COBRA addresses uncertainty in some C-R functions by using two separate approaches to estimate the incidence of mortality and nonfatal heart attacks and reports high and low values. The valuation function that accounts for a majority of the benefits is the value of a statistical life, which is a well-established value that has been used in many EPA regulatory analyses.[22]

Uncertainty in Modeling into the Future

The baselines used in AVERT are constructed from emissions and generation data reported to EPA for the year 2017. Estimating health benefits for future years using 2017 BPK values results in some uncertainty. EPA suggests that AVERT should not be used to estimate emissions reductions more than five years into the future; this limitation is discussed in the *Limitations* section, below. In most cases, forecasting the electricity sector is based on assumptions about future fuel prices, emissions constraints, electricity markets, and technological advancements, as well as other aspects of the U.S. economic and regulatory systems. These factors can be used in sophisticated analyses to forecast retirements and additions of EGUs and determine dispatch. AVERT, however, does not take these factors into account, which limits its ability to forecast changes in emissions in the future. The average emissions rates from electricity generation have been declining over the past several years for most regions. If these trends continue, the 2017 BPK values would be an overestimate of the benefits of EE/RE in future years.

Limitations

The BPK values are subject to the same limitations as the results of the AVERT and COBRA tools. Limitations discussed in this section include the timeframe for which the BPK values may be used; types of projects, programs, or policies that can be evaluated; modeling limitations regarding the curtailment of renewables; modeling limitations regarding energy storage; pollutants that are included in the analysis; and benefits beyond the scope of the tools.

Timeframe of the BPK Values

Estimates of emissions reductions from AVERT are based on actual 2017 emissions data reported to EPA by EGUs 25 MW or larger, while the emissions baseline in COBRA is based on a projection for 2017. Therefore, there are limitations in using the estimates produced by these tools to evaluate projects, programs, and policies into the future. For example, if the electricity grid continues to get cleaner, resulting in fewer emissions per kWh of generation, the BPK

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[21] For more information on other more sophisticated options for modeling health benefits for energy efficiency and renewable energy, see chapter 4 of the EPA report, *Quantifying the Multiple Benefits of Energy Efficiency and Renewable Energy: A Guide for State and Local Governments*, https://www.epa.gov/statelocalenergy/quantifying-multiple-benefits-energy-efficiency-and-renewable-energy-guide-state.

[22] For more information on the value of a statistical life, please see EPA's Mortality Risk Valuation web page at https://www.epa.gov/environmental-economics/mortality-risk-valuation.

values would decrease. EPA recommends not using AVERT to evaluate scenarios more than five years into the future; the BPK values have a similar limitation. The emission rates at EGUs will likely continue to change in the coming years, in response to regulations, fuel prices, and changes in electricity demand, such as from electric vehicles. These BPK values should therefore not be used to estimate the benefits of EE/RE past 2022.

EPA has also explored the development of BPK values for future years. As EE/RE projects, programs, and policies are often planned years in advance, it would be useful to have BPK values that are based on electricity and emissions modeling projections for years after 2022 (the limit of the 2017 values). However, EPA decided to focus on the development of the 2017 BPK values before developing a set of future values. Future BPK values, if developed, will be based on the most up-to-date electricity and emissions modeling that is available to EPA.

Project, Program, or Policy to Be Evaluated

EPA advises against using AVERT to estimate emissions reductions for projects that are too small (~ 1 MW) or too big (no greater than 15 percent of regional fossil demand). The absolute amount can differ by region but can be as low as 1,000 MW. For this reason, the BPK values will have the same limitations in terms of the size of the project, program, or policy for which they can be used.

In addition, as mentioned above, EPA modeled the EE at peak scenario by reducing generation only during 12 p.m. to 6 p.m. on weekdays. If a particular EE measure reduces demand during a very different time, such as only during the hottest days of the summer, then the benefits per kWh may be different, as discussed in *Appendix C*.

Modeling Limitations Related to Curtailing Renewable Energy Generation

AVERT estimates emissions reductions resulting from the displacement of fossil fuel-generating units by sources of EE/RE. However, the real-world dispatch of EGUs is not this simple, and as renewables continue to be added to the electricity supply, some states are beginning to see the curtailment of RE sources in periods of oversupply of generation. Generators are curtailed to ensure the reliability of the grid, usually when there is more electricity generation than demand or there is transmission congestion. Because fossil fuel units have higher marginal costs than renewables (due to the cost of the fuel), they are typically curtailed more often than renewables. However, in some states with a large proportion of generation from renewables, such as California, there have been curtailments of renewables.[23] Because AVERT does not model existing RE sources, it cannot capture the potential curtailment of renewables. For this reason, the emissions reductions and BPK values from EE/RE projects, programs, and policies may be overestimated.

Modeling Limitations Regarding Energy Storage

AVERT currently does not include assumptions concerning energy storage. Advancements in energy storage may make the storage of generation from renewables more viable, leading to increased displacement of different fossil fuel-generating units at different times of the day. For example, a solar panel generating during daylight hours could store its electricity for

[23] See, for example, a factsheet on curtailments from the California Independent System Operator (ISO): https://www.caiso.com/Documents/CurtailmentFastFacts.pdf.

consumption during the evening hours. It is unclear whether this limitation leads to an overestimate or underestimate of the BPK values.

Pollutants Beyond the Scope of the Tools

AVERT does not model reductions in emissions of NH_3 or volatile organic compounds (VOCs) associated with changes in electricity generation; therefore, EPA did not include changes in emissions of these pollutants in their analysis. However, the electricity generation sector was responsible for less than 1 percent of the NH_3 and VOC emissions in the United States in 2014, according to the National Emissions Inventory (EPA 2018). Similarly, COBRA does not estimate the formation of O_3; therefore, EPA did not examine the health impacts due to changes in O_3 concentrations. For these reasons, the BPK values may slightly underestimate the total health benefits of emissions reductions from EE/RE projects, programs, and policies. It should be noted that EPA's retrospective analysis of the CAA found that approximately 85 percent of the public health benefits of air quality regulations are due to PM reductions, rather than O_3 reductions (EPA 2011b).

AVERT does model emissions of CO_2; however, EPA chose not to include reductions of CO_2 in this analysis. Reductions in CO_2 are generally only included in studies that assess climate and welfare impacts in addition to public health impacts, which is beyond the scope of this study. Although emissions of CO_2 and climate change may be linked with some public health impacts, such as increased heat stress or incidence of vector-borne diseases, COBRA does not estimate those particular health impacts. The health impacts due to EE/RE projects, programs, and policies and corresponding BPK values may therefore be underestimated.

Benefits Beyond the Scope of the Analysis

Finally, COBRA estimates and values health benefits due to emissions reductions, but it does not include other types of benefits, such as avoiding damages from decreased timber and agricultural yields, reduced visibility, accelerated depreciation of materials, and reductions in recreation services. For this reason, the BPK values presented here may be an underestimate compared to similar values calculated using other tools that include both health and welfare benefits, such as the AP2 Model (Muller and Mendelsohn 2018).

Results

In this section, EPA presents the results of the electricity and emissions modeling, as well as the BPK values for 2017.

Emissions Reductions

EPA's AVERT was used to estimate changes in fossil-generated electricity and emissions reductions from EE/RE projects, programs, and policies. AVERT outputs used in this analysis include displaced generation (MWh) and emissions reductions of SO_2, NO_X, and $PM_{2.5}$ (tons). Complete regional-level outputs from AVERT can be found in *Appendix G: Detailed Benefits-per-kWh Results*.

On average, the SO_2 emissions reductions from EE/RE are approximately 0.85 lbs. per megawatt hour (MWh), with large regional variation. In general, the regional variation in emissions reductions is greater than the variation across EE/RE technology types. The California region has the smallest reduction in SO_2 emissions per MWh for all types of EE/RE projects, programs, and policies (Figure 3). In 2017, the largest reduction in SO_2 emissions per MWh for all types of EE/RE occurred in the Upper Midwest region. In six of the ten regions, wind projects delivered the largest SO_2 reductions per MWh. EE at peak projects show the largest SO_2 reductions per MWh in the Northeast and Southeast, and solar projects deliver the largest reductions in the Great Lakes/Mid-Atlantic and Pacific Northwest regions. EE at peak projects resulted in the lowest SO_2 reductions per MWh in six of the ten regions.

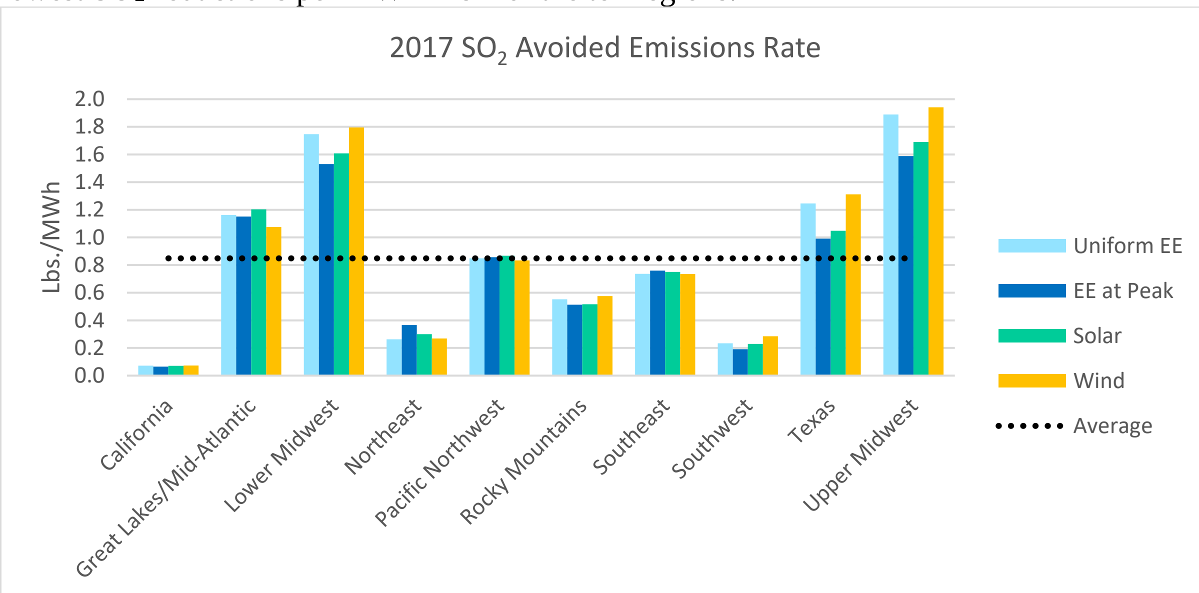

Figure 3. Avoided SO2 Emissions Rates for EE/RE Projects, Programs, and Policies in 10 AVERT Regions in 2017.

There is also substantial regional variation in the NO_x avoided emissions rates, with an average of 0.91 lbs./MWh in 2017. The California region again has the smallest reduction in NO_x emissions per MWh; and the Rocky Mountain region sees the largest reduction in emissions for all types of EE/RE projects, programs, and policies, except EE at Peak (Figure 4). EE at peak projects result in the largest NO_x emissions reduction per MWh in the majority of the regions, with wind and solar projects delivering the largest reductions in the others. It also appears SO_2 and NO_x avoided emissions rates may have an inverse relationship. In all regions where the SO_2 avoided emissions rates are below average, the NO_x avoided emissions rates are higher than the SO_2 rate; and in all regions where the SO_2 avoided emissions rates are above average, the NO_x avoided emissions rates are lower than the SO_2 rate.

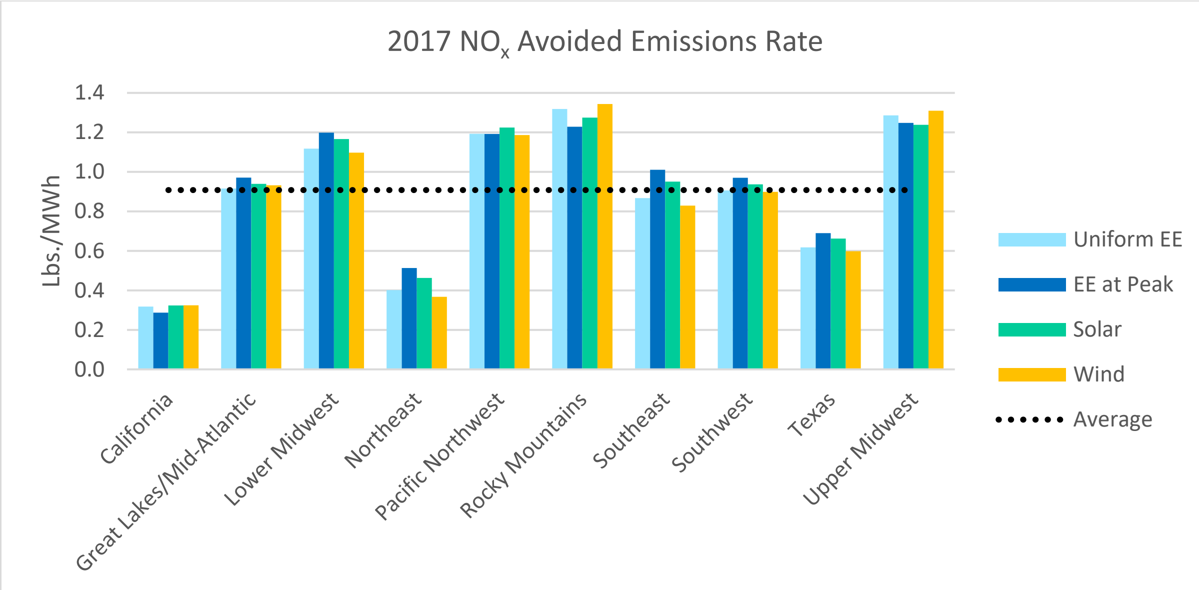

Figure 4. Avoided NO_x Emissions Rates for EE/RE Projects, Programs, and Policies in 10 AVERT Regions in 2017.

Avoided emissions rates for $PM_{2.5}$ are the lowest of the three sets of emissions rates, with an average of 0.08 lb./MWh in 2017. The Rocky Mountains region has the lowest rate of $PM_{2.5}$ reductions per MWh, at approximately 0.03 lbs./MWh; and the Great Lakes/Mid-Atlantic region has the largest rate for all regions and EE/RE types, at approximately 0.2 lbs./MWh (Figure 5). The avoided emissions rate for the Great Lakes/Mid-Atlantic region is almost double the highest rate of the other nine regions. Regions such as the Lower and Upper Midwest, which had higher-than-average SO_2 and NO_X emissions rates, have fairly low $PM_{2.5}$ rates.

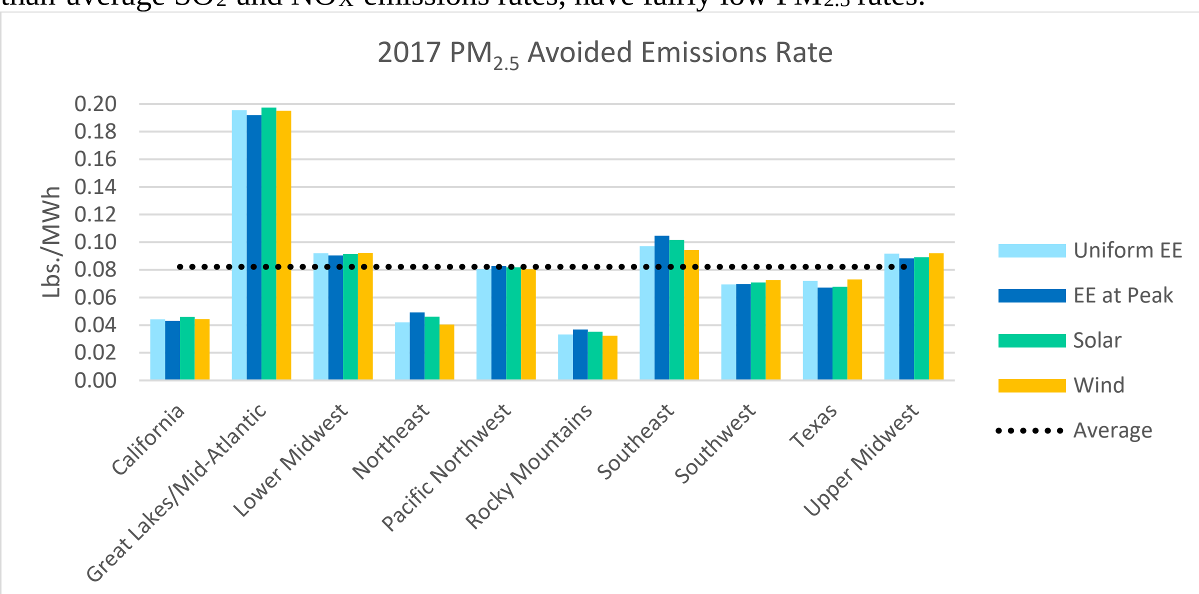

Figure 5. Avoided $PM_{2.5}$ Emissions Rates for EE/RE Projects, Programs, and Policies in 10 AVERT Regions in 2017

Benefits-per-kWh Values

The county-level emissions reductions from AVERT were entered into the appropriate counties of the COBRA tool to estimate the health benefits of each EE/RE scenario. These benefits reflect the sum of the $PM_{2.5}$ benefits from the changes in electric sector emissions of NO_x, SO_2, and $PM_{2.5}$ and reflect the range based on adult mortality functions (e.g., Krewski et al. 2009, Lepeule et al. 2012). The total health benefits from COBRA for each scenario were divided by the corresponding displaced generation values in each region as estimated by AVERT in order to calculate benefits per kWh. Values were calculated for low and high estimates using both 3 percent and 7 percent discount rates; however, only the 3 percent results are discussed in the main body of this report, as the 7 percent results have the same general trends. The low and high estimates are derived in COBRA using two different C-R functions from the literature to estimate the sensitivity of adult mortality and non-fatal heart attacks to changes in ambient $PM_{2.5}$ levels.[24] A detailed results table, including values calculated using a 7 percent discount rate, can be found in *Appendix G: Detailed Benefits-per-kWh Results*. COBRA reports results in 2017 U.S. dollars (USD).

EE/RE projects, programs, and policies in California deliver the lowest public health benefits per kWh in all scenarios (Figure 6).The largest benefits per kWh can be seen in the Great Lakes/Mid-Atlantic region, followed by the Upper Midwest. Regions such as the Pacific Northwest, Rocky Mountains, and Southwest, which had low SO_2 but high NO_x avoided emissions rates, have lower-than-average benefits per kWh. This is due in part to the fact that SO_2 converts to secondary PM in the atmosphere more readily than NO_x, and therefore results in more health impacts per ton than NO_x. The Northeast region values are of note, as EE at peak and solar projects deliver above-average benefits per kWh, despite having below-average SO_2, NO_x, and $PM_{2.5}$ emissions rates. A full list of EPA's 2017 BPK values can be found in Table 4.

[24] More information about the C-R functions used in COBRA can be found in *Appendix E: Health Impact Functions*.

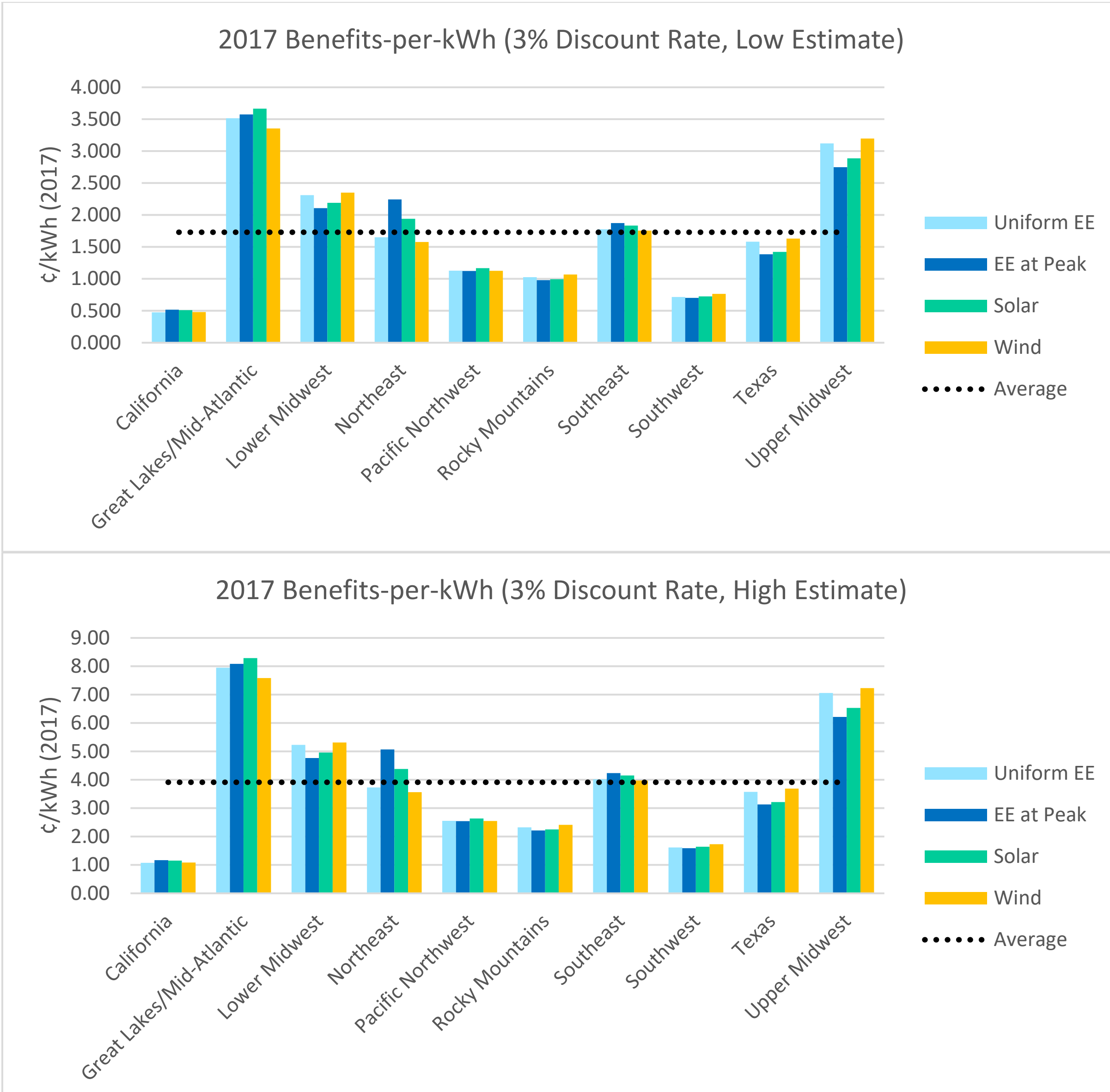

Figure 6. 2017 Benefits-per-kWh Values for EE/RE Projects, Programs, and Policies.

Table 4. 2017 Benefits-per-kWh Values (2017 USD)

Region	Project Type	3% Discount Rate		7% Discount Rate	
		2017 ¢/kWh (low estimate)	2017 ¢/kWh (high estimate)	2017 ¢/kWh (low estimate)	2017 ¢/kWh (high estimate)
California	Uniform EE	0.48	1.08	0.42	0.96
	EE at Peak	0.52	1.17	0.46	1.04
	Solar	0.51	1.15	0.45	1.03
	Wind	0.48	1.09	0.43	0.97
Great Lakes/Mid-Atlantic	Uniform EE	3.51	7.95	3.14	7.09
	EE at Peak	3.57	8.08	3.19	7.21
	Solar	3.67	8.29	3.27	7.39
	Wind	3.35	7.59	2.99	6.77
Lower Midwest	Uniform EE	2.31	5.23	2.06	4.66
	EE at Peak	2.11	4.77	1.88	4.25
	Solar	2.19	4.96	1.96	4.42
	Wind	2.35	5.32	2.10	4.74
Northeast	Uniform EE	1.65	3.73	1.47	3.33
	EE at Peak	2.24	5.07	2.00	4.52
	Solar	1.94	4.38	1.73	3.91
	Wind	1.58	3.56	1.41	3.18
Pacific Northwest	Uniform EE	1.13	2.55	1.01	2.28
	EE at Peak	1.12	2.54	1.00	2.27
	Solar	1.17	2.64	1.04	2.35
	Wind	1.13	2.55	1.01	2.27
Rocky Mountains	Uniform EE	1.03	2.32	0.92	2.07
	EE at Peak	0.98	2.21	0.87	1.98
	Solar	0.99	2.25	0.89	2.01
	Wind	1.07	2.41	0.95	2.15
Southeast	Uniform EE	1.78	4.02	1.58	3.58
	EE at Peak	1.87	4.24	1.67	3.78
	Solar	1.83	4.15	1.64	3.70
	Wind	1.76	3.98	1.57	3.55
Southwest	Uniform EE	0.71	1.62	0.64	1.44
	EE at Peak	0.70	1.59	0.63	1.42
	Solar	0.73	1.64	0.65	1.46
	Wind	0.77	1.73	0.68	1.54
Texas	Uniform EE	1.58	3.58	1.41	3.19
	EE at Peak	1.39	3.13	1.24	2.80
	Solar	1.42	3.22	1.27	2.87
	Wind	1.63	3.69	1.45	3.29
Upper Midwest	Uniform EE	3.12	7.06	2.78	6.30
	EE at Peak	2.75	6.22	2.45	5.55
	Solar	2.89	6.53	2.58	5.83
	Wind	3.20	7.23	2.85	6.45

Discussion

The BPK values represent estimates of the monetized annual public health benefits resulting from emissions reductions associated with EE/RE projects, programs, and policies. There are different values for each combination of region and EE/RE intervention type (i.e., wind, solar, uniform EE, and EE at peak). It should be noted that the total benefits from EE/RE projects, programs, and policies in any region will include health benefits both within and outside of that region.

The results show that there are larger differences in benefits per kWh across regions than across EE/RE technologies. This is likely due to differences in the fossil fuel mix used for generation across regions. For example, California has low BPK values because its generation comes largely from natural gas, which has low emissions rates. These emissions rates are similar regardless of the EE/RE technology displacing the fossil generation. However, in other regions such as the Northeast, there is more variation across technology types. In the case of the Northeast, the fossil generation operating during the peak period has higher emissions rates than the generation operating during other times of the day. Therefore, EE at peak and solar power, which displace generation during the daytime peak hours, have higher benefits per kWh than wind or uniform EE, which displace generation in more hours of the day. However, emissions are only one factor in the estimation of BPK values. The estimated health benefits are also affected by the population of the areas impacted by the emissions reductions. Areas with more people affected by changes in air quality will have a greater cumulative health benefit. For example, the Southwest has higher NO_x and $PM_{2.5}$ emissions rates than the Northeast, although both regions have similar SO_2 rates. However, the Northeast has larger benefits per kWh for all technology types; this is due in part to the Northeast's higher population density relative to the Southwest.

In most cases though, the regional variation in BPK values is driven by differences in both population and emissions rates. For example, the Upper Midwest has higher avoided SO_2 and NO_x emissions rates compared to the Great Lakes/Mid-Atlantic region in 2017. However, the Great Lakes region has 5 to 30 percent higher BPK values compared to the Upper Midwest. There are several possible reasons for this, including that the avoided $PM_{2.5}$ emissions rates in the Great Lakes/Mid-Atlantic region are approximately double those in the Upper Midwest, and that the Great Lakes/Mid-Atlantic region is more densely populated than the Upper Midwest region.

The BPK values presented here are similar in magnitude to values reported in the literature. McCubbin and Sovacool (2013) found that wind generation in California between 1987 and 2006 delivered 0.4¢/kWh to 4.7¢/kWh in health benefits. EPA's low California results are similar to these results, approximately 0.4¢/kWh, but the high estimate (1.1¢/kWh) is more than double McCubbin and Sovacool's (2013) estimate. Buonocore et al. (2016) examined EE/RE benefits in New Jersey and Maryland, an area similar to EPA's Great Lakes/Mid-Atlantic region. Again, EPA's results are similar, but slightly lower for all technology types, except EE at peak, compared to those seen in the literature review (Table 5).

Table 5. Comparison of EPA and Buonocore et al. (2016) Benefits-per-kWh Values

Project Type	Buonocore et al. Results for New Jersey and Maryland (2012 ¢/kWh)	EPA Results for Great Lakes/Mid-Atlantic Region (2017 ¢/kWh)
Uniform EE[a]	9.4–15	3.1–7.9
EE at Peak[a]	1.4–10	3.2–8.1
Solar	6.3–15	3.3–8.3
Wind	8.1–17	3.0–7.6

[a] *Referred to as baseload or peak demand side management (DSM) in the Buonocore et al. study.*

In addition to being similar to other BPK values from the literature, EPA's results are similar to the cost of EE/RE projects, programs, and policies. This suggests that the health benefits of EE/RE projects, programs, and policies can help offset all or part of the cost of these technologies. According to a study by the LBL (2015), the average cost of "saved electricity" or EE is 0.046¢/kWh (Figure 7; 2012 USD). EPA's estimates for the benefits of EE projects range from 0.4¢/kWh (1.2¢/kWh) in California to 4.0¢/kWh (8.0¢/kWh) in the Great Lakes/Mid-Atlantic region using the low and high estimates.

The BPK values are also largely similar to the cost of new RE capacity. According to Lazard's annual Levelized Cost of Energy Analysis, the cost of wind energy is between 3.0¢/kWh and 6.0¢/kWh, and the cost of utility scale solar is between 4.3¢/kWh and 5.3¢/kWh (Lazard 2017). According to EPA's results, the average benefits per kWh for both wind and solar projects are approximately 1.6¢/kWh and 3.7¢/kWh for the low and high values, respectively. Therefore, without considering any of the other non-health benefits of EE/RE technologies, up to half of the costs of wind and solar projects could be covered by EPA's low health benefit estimates, and nearly all of the costs could be covered by EPA's high health benefit estimates. For some regions, the health benefits of EE/RE entirely outweigh their costs. For example, the high estimates, using both the 3 and 7 percent discount rates, for wind projects in the Great Lakes/Mid-Atlantic region are greater than Lazard's (2017) levelized costs; the high estimate BPK values in the Upper Midwest are also larger than the levelized costs for wind energy. Similarly, the BPK values (high estimates, 3 percent discount rate) for solar projects in the Lower Midwest, Great Lakes/Mid-Atlantic, and Upper Midwest regions are greater than or equal to the higher end of the levelized costs.

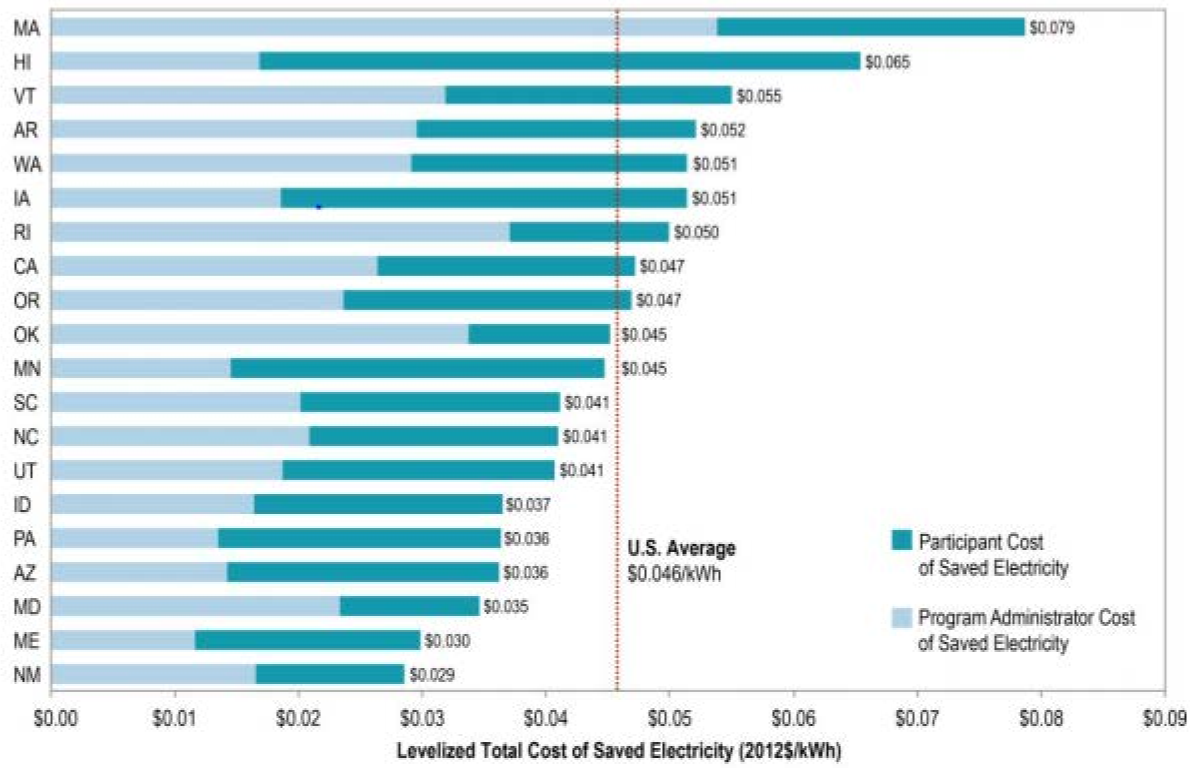

Figure 7. Levelized Cost of EE Programs by State. Source: LBL 2015.

By generating these health benefits per kWh values for EE/RE, EPA hopes to address the gap in the literature and provide health BPK values that cover all regions in the United States and cover key EE/RE project, program, and policy types. Such health benefits estimates may have several uses. For example, state public utility commissions (PUCs) and state energy offices (SEOs) may use estimates of the monetized public health benefits of EE as an input to portfolio-level, cost-benefit analyses; or program-specific, cost-effectiveness tests. Policymakers or financial institutions could also use these estimates to develop a fuller accounting of the benefits of investments in EE/RE. Finally, EE/RE developers, state and local public health administrators, NGOs, and the general public can use these estimates to quantify the public health benefits of existing or proposed EE/RE projects, programs, and policies. Please note that this is not an exhaustive list of uses for BPK values. Furthermore, because the BPK values provide a screening-level estimate, they may not be appropriate for certain analyses, such as federal air quality rulemaking.

In addition, as discussed in the *Limitations* section on page 16, one area of additional research includes developing BPK values for future years. Such values would be based on modeling the electricity sector to estimate emissions rates in future years and would allow for the projection of benefits from EE/RE projects, programs, and policies in years beyond 2022 (the current limit of the 2017 values).

Conclusions

State and local governments are increasingly interested in quantifying the public health value of emissions reductions from EE/RE so that they can fully reflect these benefits in policy decision-making processes. Some studies have quantified the benefits but have used different approaches and assumptions, making it difficult for others to adopt or credibly compare the health benefits estimates on a per-kWh basis.

EPA has developed regional-level BPK screening values to further these analyses and fill the gap for this type of analysis in the literature. By using the AVERT and COBRA tools, EPA developed regional BPK values for uniform EE, EE at peak, wind, and solar projects, programs, and policies, which incorporate the benefits of SO_2, NO_x, and $PM_{2.5}$ emissions reductions. Although results vary by region, on average, EPA found that EE/RE programs delivered benefits of 1.7¢/kWh to 3.9¢/kWh in the United States in 2017 (using a 3 percent discount rate).

EPA believes that these health benefit screening values may be useful to a wide range of stakeholders seeking to estimate the public health benefits of EE/RE projects, programs, and policies, including state PUCs, SEOs, policymakers, financial institutions, EE/RE developers, state and local public health administrators, NGOs, and the general public.

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Appendix A: AVoided Emissions and geneRation Tool (AVERT)

AVERT analyzes changes in fossil-fired electricity generation from solar, wind, and EE programs in 10 unique regions of the continental United States (Figure A - 1).[25] The AVERT regions take into account the fact that customers' electricity demand is met jointly by generation resources throughout a region, rather than from a single power plant.[26] AVERT provides estimates of changes in NO_x, SO_2, $PM_{2.5}$, and CO_2 emissions at the regional, state, and county levels.

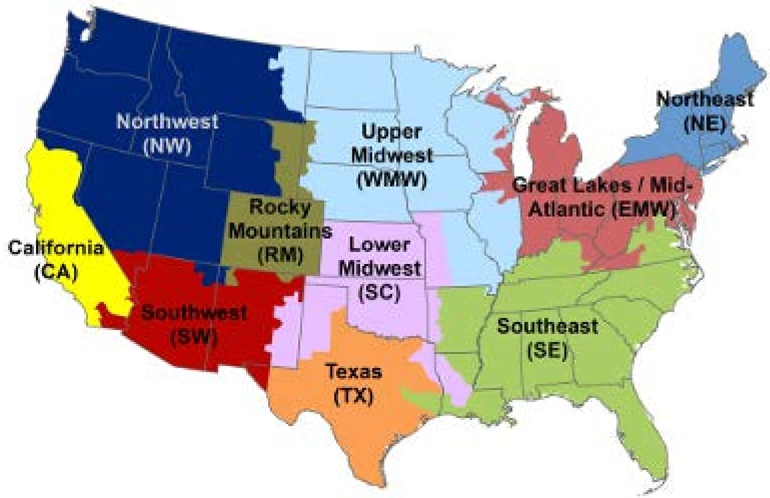

Figure A - 1. AVERT Regions

In AVERT, the impacts on emissions from wind and solar electricity generation are modeled using the annual electricity generation capacity in MWs of the renewable project. AVERT uses these capacity inputs to estimate the amount of electricity generation (in megawatt hours) the project(s) would produce. Capacities can be entered separately for wind and two types of solar installations: utility-scale and rooftop.

AVERT uses hourly data reported to EPA's CAMD by EGU. Data are available from 2007 to 2017. These data include gross generation; steam output; heat input; and emissions of SO_2, NO_x, and CO_2. Hourly emissions of $PM_{2.5}$ are calculated using data from the National Emissions Inventory.

AVERT uses hourly data on NO_x, SO_2, and CO_2 emissions to estimate the impact of EE/RE projects, programs, and policies on emissions. AVERT uses the hourly generation data to determine the probability of whether a particular unit will be operating in a given hour of the year. The tool also uses hourly emissions data to estimate the emissions from electricity generation from that unit. AVERT provides built-in assumptions about the capacity factors of RE technologies to estimate the annual amount of generation an RE project will produce, and the likely hours in which it will be operating.[27] For example, AVERT uses data from the National Renewable Energy Laboratory to estimate the likely hours of the year a solar project would generate electricity in each region. Users are able to develop their own site- or region-specific

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[25] Although in some regions solar or hydroelectricity may be on the margin, AVERT assumes they are must-take resources and fossil-fired electricity generators are the only generators affected by increased EE/RE.

[26] Note that while there are imports and exports of electricity across regions, AVERT does not explicitly model these transfers.

[27] AVERT reflects regional capacity factors for renewable generation, based on actual wind projects from AWS Truepower and solar projects modeled in the National Renewable Energy Laboratory's PV Watts tool, reflecting the availability of sun and wind resources in each region. See Appendix C of AVERT's user manual for details.

renewable energy load profiles for use in AVERT; however, this study used the built-in capacity factor assumptions. For EE projects, programs, and policies, the hours of the year they reduce electricity demand can be input directly by the user or it can be based on the top hours of demand in each region.

AVERT then determines which fossil units would likely be operating during the hours that the EE/RE project, program, or policy is operating or reducing demand, to determine the units that would be displaced by the EE/RE project, program, or policy. AVERT estimates the emissions reductions that would occur as a result of that displacement based on the emissions rate at each unit. The resulting estimated reductions in generation and emissions are reported at the county, state, and regional levels.

Appendix B: Co-Benefits Risk Assessment (COBRA) Health Impacts Screening and Mapping Tool

COBRA v3.0 includes preloaded projected emissions baselines for 2017, which is estimated using data from EPA's 2011 Version 6.2 Air Emissions Modeling Platform (2011 v6.2 platform). Emissions from the electric generating sector in the 2011 v6.2 platform are projections of emissions in 2017 from the Integrated Planning Model (IPM) Power Sector Modeling Platform (v5.14). The air emissions platform also contains emissions projections from other sources besides EGUs, such as nonpoint sources, mobile sources, fires, and other point sources. EPA has used the emissions modeling platform for several recent air pollution rules, including the Final 2015 NAAQS for O_3, the 2011 National Air Toxics Assessment (NATA), and the proposed update to the Cross-State Air Pollution Rule (CSAPR). The 2017 emissions baselines contain projected emissions that reflect federal and state measures (promulgated or under reconsideration) as of December 2014, including:

- The CSAPR,
- A Federal regulatory measure for achieving the 1997 NAAQS for ozone and fine particles,
- The Mercury and Air Toxics Standards (MATS),
- Actions EPA had taken to implement the Regional Haze Rule,
- The Cooling Water Intakes Rule [316(b)],
- The disposal of Coal Combustion Residuals (CCR) from Electric Utilities Rule, and
- State regulations in place as of December 2014.

The assumptions underlying the emissions inventories are detailed in the Technical Support Document: Preparation of Emissions Inventories for the Version 6.2, 2011 Emissions Modeling Platform (EPA 2015).

COBRA also includes a reduced-form air quality model, the Phase II S-R Matrix, to estimate how changes in air pollution emissions impact ambient air quality. The S-R Matrix is based on the Climatological Regional Dispersion Model (CRDM) and consists of fixed-transfer coefficients that reflect the relationship between emissions at source counties and ambient air pollution concentrations at receptor locations. To calculate the pollutant concentration at a destination county, transfer coefficients are used in the following equation:

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

Where:

D_j^s = Concentration of pollutant *s* at destination county *j* (ug/m^3)

$E^s_{i,c}$ = Emission of pollutant *s* from emissions category *c* in source county *i* (tons/year)

$T^s_{c,i,j}$ = Transfer coefficient for pollutant *s* from source county *i* to destination county *j* from 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)

Ionic conversion factors used in the equation above are molecular weight ratios. These are used to adjust the transfer coefficients to reflect the concentration of precursors to secondarily formed particulate species. Standard molecular weights and ionic conversion factors are listed in Table B - 1 and Table B - 2.

Table B - 1. Standard Molecular Weights

Species	Symbol	Standard Molecular Weight
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	46.055
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

Table B - 2. Ionic Conversion Factors

Species	Ionic Conversion Factors
$PM_{2.5}$, Secondary Organic Aerosols	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

COBRA accounts for the formation of secondary $PM_{2.5}$ from NO_x and SO_2 emissions through atmospheric chemistry and air pollution transport.[28, 29] COBRA focuses only on primary and secondary $PM_{2.5}$, and it does not currently estimate the formation of other pollutants such as O_3. Secondary $PM_{2.5}$ is formed when sulfate (SO_4^{2-}) and nitrate (NO_3^-) ions react with ammonium (NH_4^+) to form ammonium bisulfate (NH_4HSO_4), ammonium sulfate [$(NH_4)_2SO_4$], and ammonium nitrate (NH_4NO_3). In COBRA, NH_4^+ reacts first with SO_4^{2-} to form NH_4HSO_4 and $(NH_4)_2SO_4$. If any NH_4^+ remains, it then reacts with NO_3^- to form NH_4NO_3. As this method is simpler than the modeling completed using more sophisticated air quality models, COBRA results are also calibrated to measured $PM_{2.5}$ concentration data obtained from EPA for 2011. Again due to the uncertainty surrounding the S-R Matrix, COBRA is treated as a screening-level tool.

[28] The ambient pollution in a given area is a result of local and upwind pollutant emissions. Winds can transport pollutants across state and regional boundaries, so emissions reductions in one region often affect air quality and human health in downwind regions.

[29] For more information about the S-R Matrix used by COBRA, see the User's Manual for the COBRA Health Impact Screening and Mapping Tool, Appendix A (https://www.epa.gov/statelocalenergy/users-manual-co-benefits-risk-assessment-cobra-screening-model).

Once COBRA estimates the changes in $PM_{2.5}$ concentrations at the county level, it then uses C-R functions to determine the change in public health impacts from a change in ambient air quality. The C-R functions embedded in COBRA are taken from epidemiological studies; and are consistent with the methods used by EPA to estimate the health impacts of air pollution rules, including MATS.[30] The output of these functions is the number of avoided premature deaths, heart attacks, hospital admissions for respiratory and cardiovascular-related illnesses, incidences of acute bronchitis, upper and lower respiratory symptoms, asthma exacerbations or emergency room visits, minor restricted activity days, and illness-related work loss days. See *Appendix E* for a list of the epidemiological studies and more information about the C-R function used in COBRA.

Finally, COBRA applies estimates of the value of avoiding public health impacts to determine the monetary benefits associated with reductions in air pollution. Values used in COBRA were used in recent EPA RIAs, including analyses for the rule mentioned above. They were derived using a variety of methods that estimate how much people are willing to pay to reduce the risk of a health incident or the cost of illness (COI), which includes direct medical costs and opportunity costs.[31] The value of avoiding premature adult mortality, also known as the value of a statistical life (VSL), is generally responsible for more than 95 percent of the monetized benefits of emissions reductions. The VSL used in COBRA to estimate the value of avoided adult mortality ranges from approximately \$7.5 million to \$8.4 million (in 2010 USD), assuming a discount rate of seven percent and three percent, respectively. This VSL value, based on 26 published studies, is identical to the values used by EPA in regulatory analyses of air pollution rules. The value of other health impacts, such as non-fatal heart attacks, hospitalizations, and asthma exacerbations, are smaller and based on the COI. For example, the value of non-fatal heart attacks ranges between \$31,446 and \$263,795, and the value of hospital admissions ranges between \$15,430 and \$41,002 per incident. See *Appendix F* for a complete list of the values used in COBRA.

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[30] For a complete list of recent RIAs of EPA air pollution rules, see https://www.epa.gov/economic-and-cost-analysis-air-pollution-regulations/regulatory-impact-analyses-air-pollution. Many of these analyses use a benefits-per-ton approach, developed by EPA (Fann et al. 2012). COBRA uses most of the same C-R functions as those used in the benefits-per-ton approach. For a list and description of the epidemiological studies used by COBRA to estimate adverse health effects, see the User's Manual for the COBRA Health Impact Screening and Mapping Tool, Appendix C (https://www.epa.gov/statelocalenergy/users-manual-co-benefits-risk-assessment-cobra-screening-model).

[31] For more information about the economic values used by COBRA to estimate the economic value of avoiding adverse health effects and how they were derived, see the User's Manual for the COBRA Health Impact Screening and Mapping Tool, Appendix F (https://www.epa.gov/statelocalenergy/users-manual-co-benefits-risk-assessment-cobra-screening-model).

Appendix C: Sensitivity Analyses on Project, Program, or Policy Size and Peak Energy-Efficiency Definition

EPA conducted sensitivity analyses using AVERT and the COBRA tool to determine the extent to which modeling scenario assumptions might impact the BPK results. EPA analyzed two different types of potential sensitivity: the size of the EE/RE project, program, or policy studied; and the definition of EE at peak.

Sensitivity Analysis on Project, Program, or Policy Size Assumptions

EPA examined the potential sensitivity of the BPK values to assumptions about project size by modeling BPK values for five different project sizes: from 100 MW to 2,000 MW added capacity for the wind and utility solar modeling options in AVERT, and from 100 GWh to 2,000 GWh of displaced generation for the EE modeling options.

The results of these model runs illustrate that there is a strong linear relationship between project size and emissions reductions (R^2 = 0.9996–1.0, Figure C - 1). The results from AVERT were then input into COBRA to assess the sensitivity of emissions reductions on health impacts. These results also show that there is a strong linear relationship between the amount of emissions reductions and health impacts (Figure C - 2).

The results of this sensitivity analysis indicate that the project size does not have a large impact on the marginal BPK results (i.e., a larger project does not generate disproportionately larger marginal benefits or have a higher BPK result than a smaller project). The resulting BPK values from these model runs with different project sizes are consistent with this; for each region and project, program, or policy type modeled, the results are within 0.1¢ per kWh (Table C - 1). As a result, this analysis presents BPK values modeled using only a single assumption about project size.

Note, however, an extremely large EE/RE project, program, or policy could displace more than the marginal EGUs and extend into the baseload units, which may have a different emissions profile. See the *Limitations* section on page 16 of this report for more information about the limitations on project size for which the BPK values should be used.

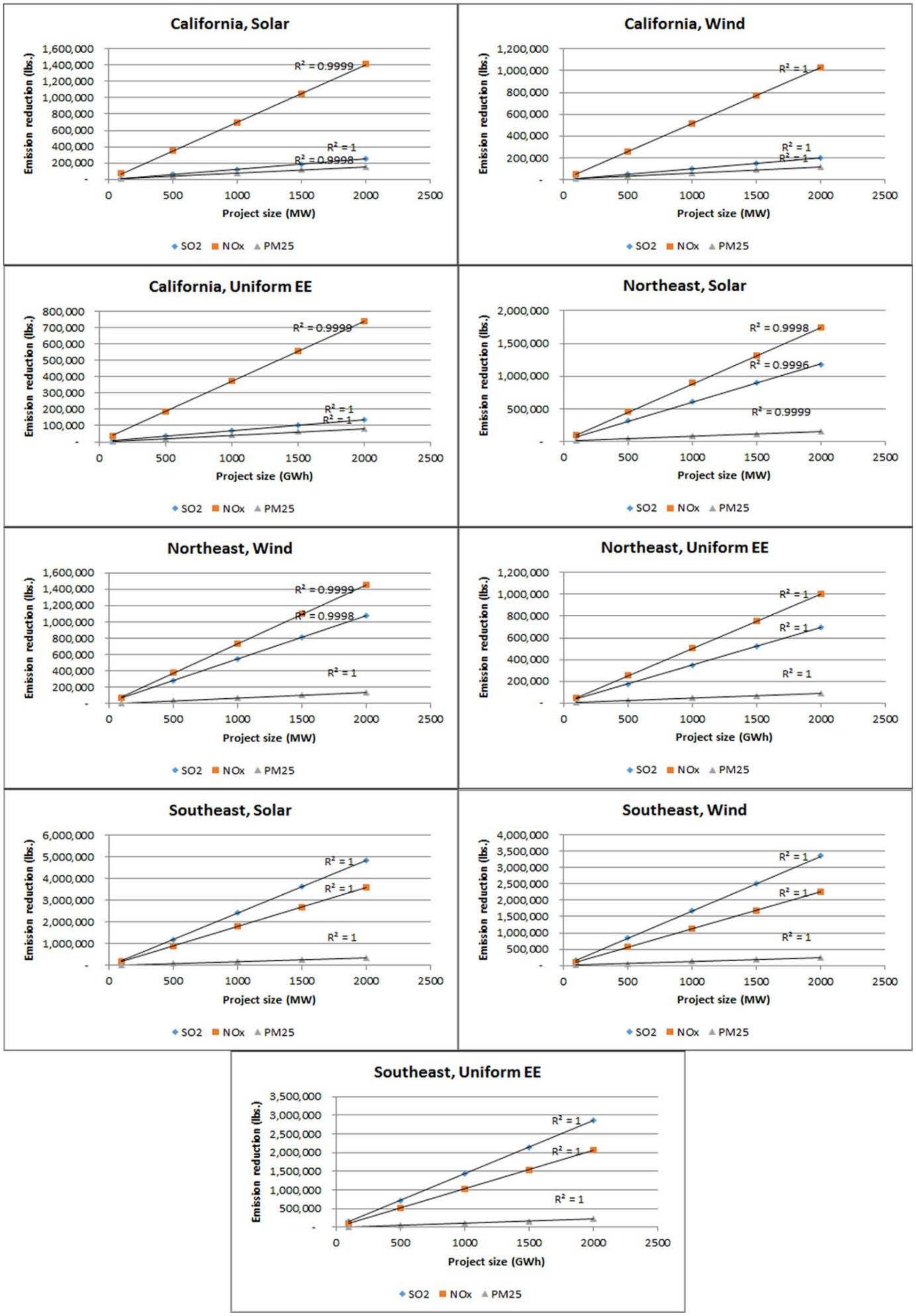


Figure C - 1. AVERT Sensitivity for Project, Program, or Policy Size.

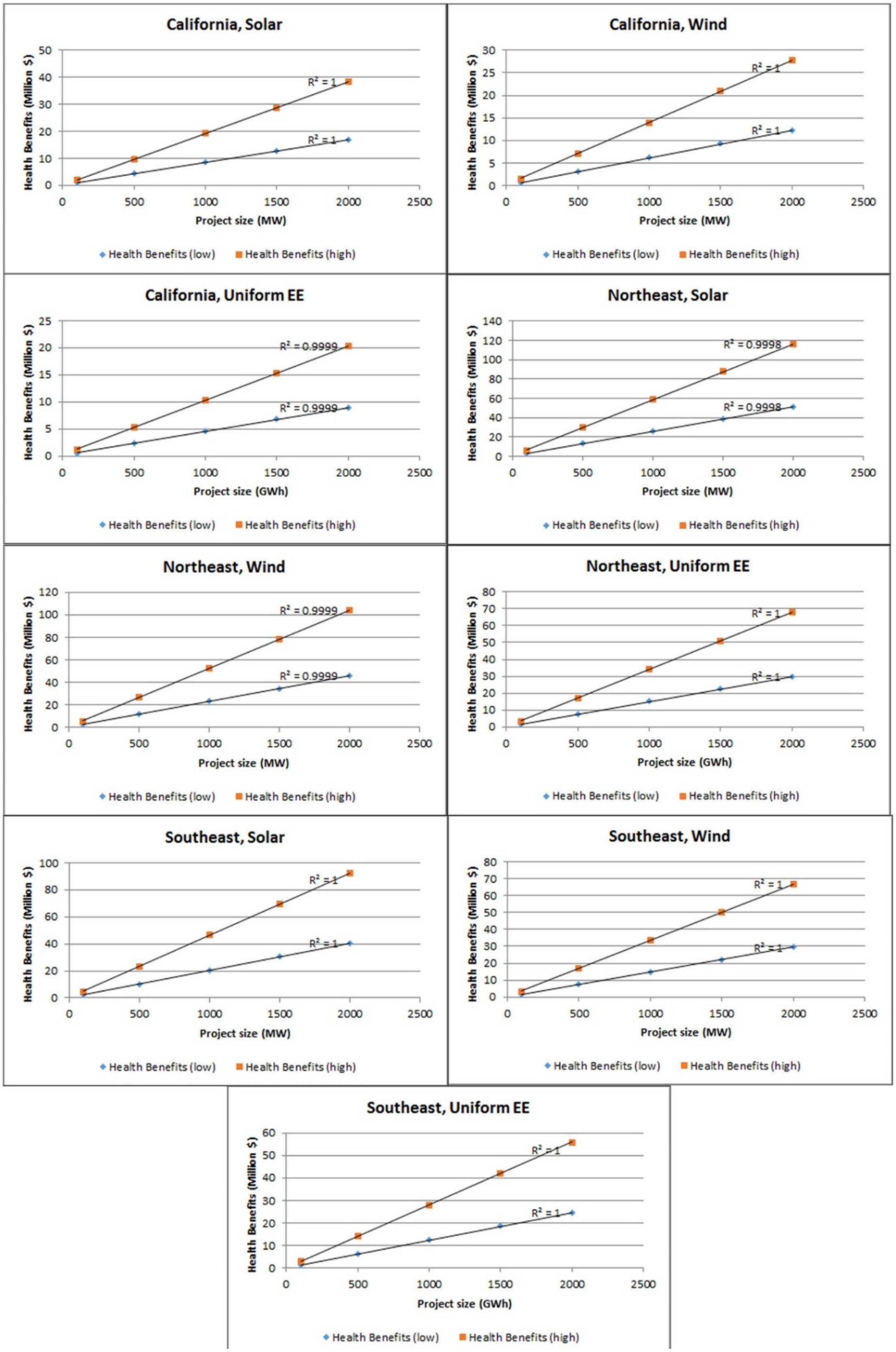


Figure C - 2. COBRA Sensitivity Analysis for Project Size.

Table C - 1. Results from Sensitivity Analysis on Project, Program, or Policy Size.

				Emissions Reductions (tons) from AVERT			Health Benefits (million USD) from COBRA		Benefits per kWh (¢/kWh)	
Region	Project Type	Capacity (MW/GWh)	Displaced Generation (MWh)	SO_2	NO_x	$PM_{2.5}$	Health Benefits (low)	Health Benefits (high)	Low Estimate	High Estimate
Southeast	Wind	100	120,370	84	56	6	1.67	3.77	1.4	3.1
		500	602,150	418	281	30	8.33	18.86	1.4	3.1
		1,000	1,204,500	837	562	60	16.60	37.58	1.4	3.1
		1,500	1,806,580	1,256	842	91	24.85	56.25	1.4	3.1
		2,000	2,408,940	1,676	1,124	121	33.06	74.83	1.4	3.1
	Solar	100	169,440	121	90	9	2.33	5.28	1.4	3.1
		500	847,250	601	449	46	11.52	26.08	1.4	3.1
		1,000	1,694,380	1,205	897	92	22.96	51.98	1.4	3.1
		1,500	2,541,750	1,807	1,342	137	34.27	77.57	1.3	3.1
		2,000	3,388,780	2,408	1,788	183	45.52	103.04	1.3	3.0
	Uniform EE	100	104,950	72	51	5	1.40	3.17	1.3	3.0
		500	524,940	359	257	27	6.99	15.81	1.3	3.0
		1,000	1,049,980	716	514	54	13.90	31.47	1.3	3.0
		1,500	1,575,040	1,073	771	82	20.79	47.06	1.3	3.0
		2,000	2,099,990	1,432	1,027	109	27.64	62.57	1.3	3.0
California	Wind	100	152,050	5	26	3	0.75	1.69	0.5	1.1
		500	761,630	25	129	15	3.55	8.02	0.5	1.1
		1,000	1,522,830	50	257	30	6.93	15.67	0.5	1.0
		1,500	2,284,090	75	386	45	10.35	23.39	0.5	1.0
		2,000	3,044,890	99	514	60	13.75	31.09	0.5	1.0
	Solar	100	194,640	6	36	4	1.04	2.34	0.5	1.2
		500	971,730	31	174	19	4.84	10.94	0.5	1.1
		1,000	1,945,550	62	346	39	9.51	21.50	0.5	1.1
		1,500	2,923,700	93	523	59	14.26	32.22	0.5	1.1
		2,000	3,899,550	126	704	79	18.98	42.93	0.5	1.1
	Uniform EE	100	104,510	3	19	2	0.56	1.27	0.5	1.2
		500	522,680	17	94	10	2.65	5.99	0.5	1.1
		1,000	1,045,830	34	187	21	5.13	11.59	0.5	1.1
		1,500	1,568,940	51	279	31	7.59	17.16	0.5	1.1
		2,000	2,091,230	68	369	41	10.02	22.66	0.5	1.1

				Emissions Reductions (tons) from AVERT			Health Benefits (million USD) from COBRA		Benefits per kWh (¢/kWh)	
Region	**Project Type**	**Capacity (MW/GWh)**	**Displaced Generation (MWh)**	**SO_2**	**NO_x**	**$PM_{2.5}$**	**Health Benefits (low)**	**Health Benefits (high)**	**Low Estimate**	**High Estimate**
Northeast	Wind	100	174,470	29	37	3	2.72	6.14	1.6	3.5
		500	873,200	141	187	17	13.37	30.20	1.5	3.5
		1,000	1,748,100	275	369	35	26.24	59.26	1.5	3.4
		1,500	2,620,800	407	549	52	38.81	87.64	1.5	3.3
		2,000	3,495,010	537	727	69	51.37	116.02	1.5	3.3
	Solar	100	157,170	32	46	4	3.01	6.72	1.9	4.3
		500	787,140	157	227	19	14.83	33.50	1.9	4.3
		1,000	1,573,340	306	448	39	29.42	66.45	1.9	4.2
		1,500	2,361,630	449	660	58	43.65	98.56	1.8	4.2
		2,000	3,146,030	590	869	77	57.51	129.88	1.8	4.1
	Uniform EE	100	104,880	18	25	2	1.72	3.91	1.6	3.7
		500	524,150	88	126	11	8.57	19.36	1.6	3.7
		1,000	1,048,680	175	252	23	16.99	38.36	1.6	3.7
		1,500	1,573,550	262	377	34	25.31	57.15	1.6	3.6
		2,000	2,098,790	347	501	45	33.58	75.85	1.6	3.6

Sensitivity Analysis on Definition of Peak Energy Efficiency

As discussed in the main text of this report, EPA considered two different definitions of the peak period to model EE at peak projects, programs, and policies. One approach is based on defining the peak period as certain hours of the day. The other approach is based on defining peak as the top hours of demand during the year (e.g., the top 200 hours with the highest demand).

EPA conducted two sensitivity analyses related to the definition of peak. The first examined the difference in emissions reductions based on using different hours of the day as the peak period. This sensitivity analysis modeled the same total generation reduction but spread through different hours of the day, including seasonal variations in some cases. Different hours of the day and seasonal variations were taken from the definitions of the peak period used by five electric utilities in different parts of the country (Figure C - 3). After modeling the definitions with AVERT, EPA plotted the resulting avoided emissions rates to determine whether there were large differences in emissions reductions based on differences in the hours of the day defined as the peak period. This sensitivity analysis was conducted for all AVERT regions. The results show that over the course of a year, there are only slight differences in avoided emissions rates in most regions due to differences in the hours of the day and seasons defined as the peak period (Figure C - 4). In some of the PG&E scenarios larger differences in avoided emissions rates can be seen, but this may be attributable to the fact that PG&E was the only utility to define peak hours as only occurring during the summer months. Uniform EE rates are included as a point of reference but were not used to determine the final EE at peak scenario. As a result, EPA used a single composite definition of 12 p.m. to 6 p.m. on weekdays as the definition of the peak period for modeling purposes in this analysis.

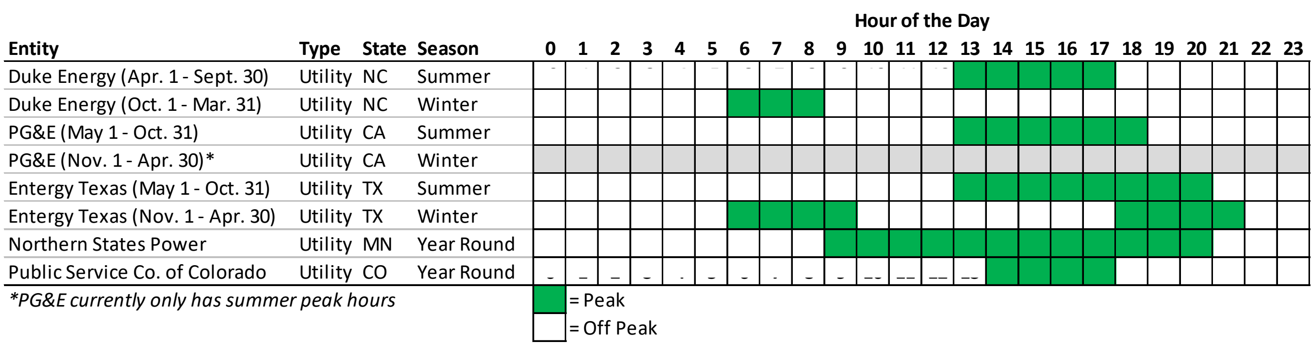
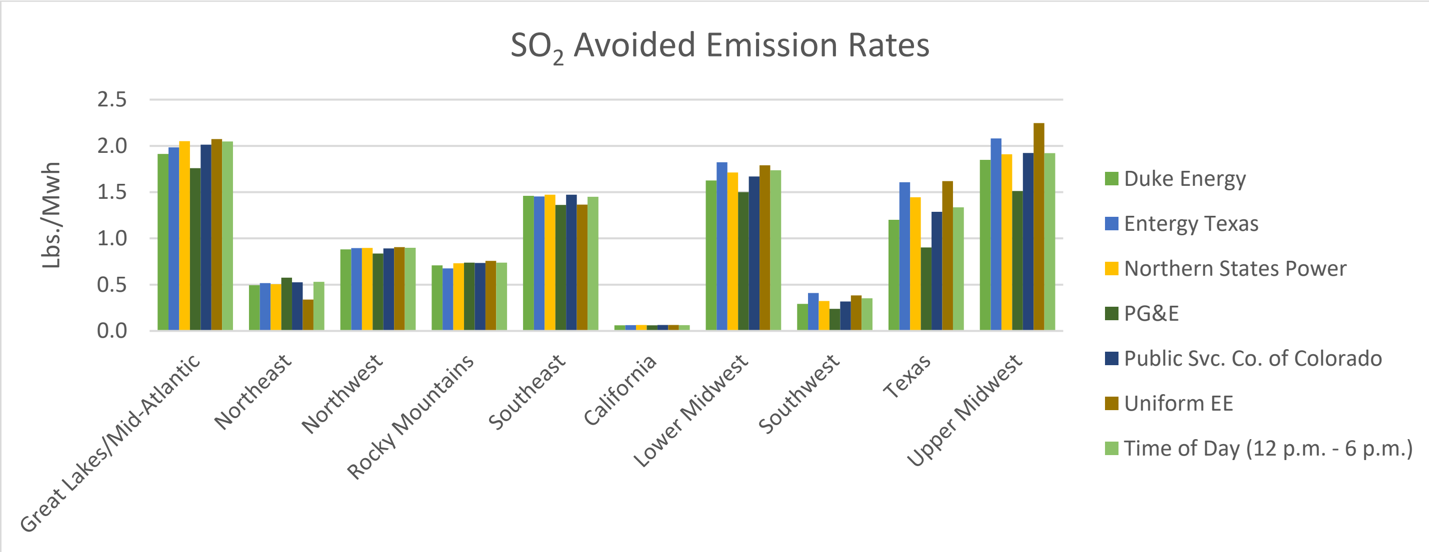
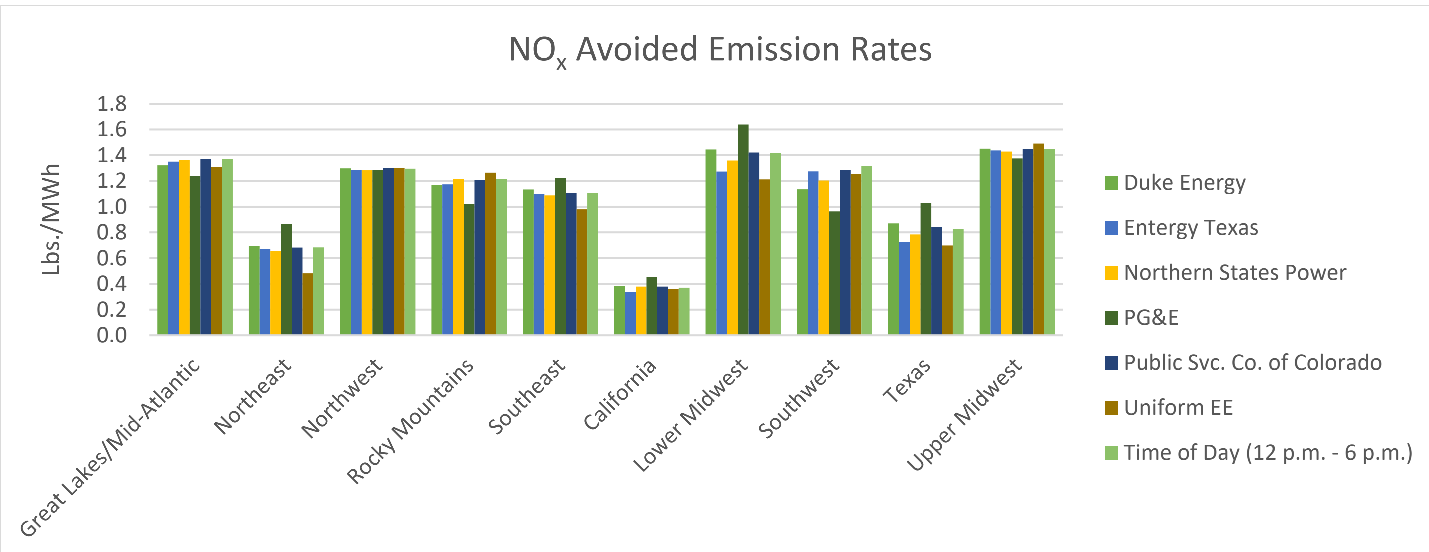


Figure C - 3. Definitions of Peak Hours from Different Entities in the Electric Sector.

EPA also conducted a sensitivity analysis to determine the difference in emissions reductions using an hour-of-day approach to define the peak period compared to using a top-hours-of-demand approach. In this case, EPA modeled the same generation reduction, but spread it differently in different hours of the year. In the hour-of-day approach, EPA reduced generation only during 12 p.m. to 6 p.m. on weekdays. In the top-hours-of-demand approach, EPA used the same total generation reduction but spread the reductions only to the top 200 hours of demand. The results show large differences in many regions in the emissions reductions resulting from the same amount of generation reduction, depending on whether the hour-of-day approach or top-hours-of-demand approach was used to define the peak period (Figure C - 5). For example, in the Northeast, using the top-hours-of-demand approach results in much higher emissions reductions compared to the hour-of-day approach. This is likely due to the use of distillate oil backup units that are used in the Northeast during periods of high demand. When the generation reductions are confined only to this period, it affects only these high-emitting units. Nevertheless, as discussed in the report, EPA chose to use the hour-of-day approach to define the peak period, as EPA determined it to be the more relevant definition for most EE/RE projects, programs, and policies based on expected uses for the BPK values.





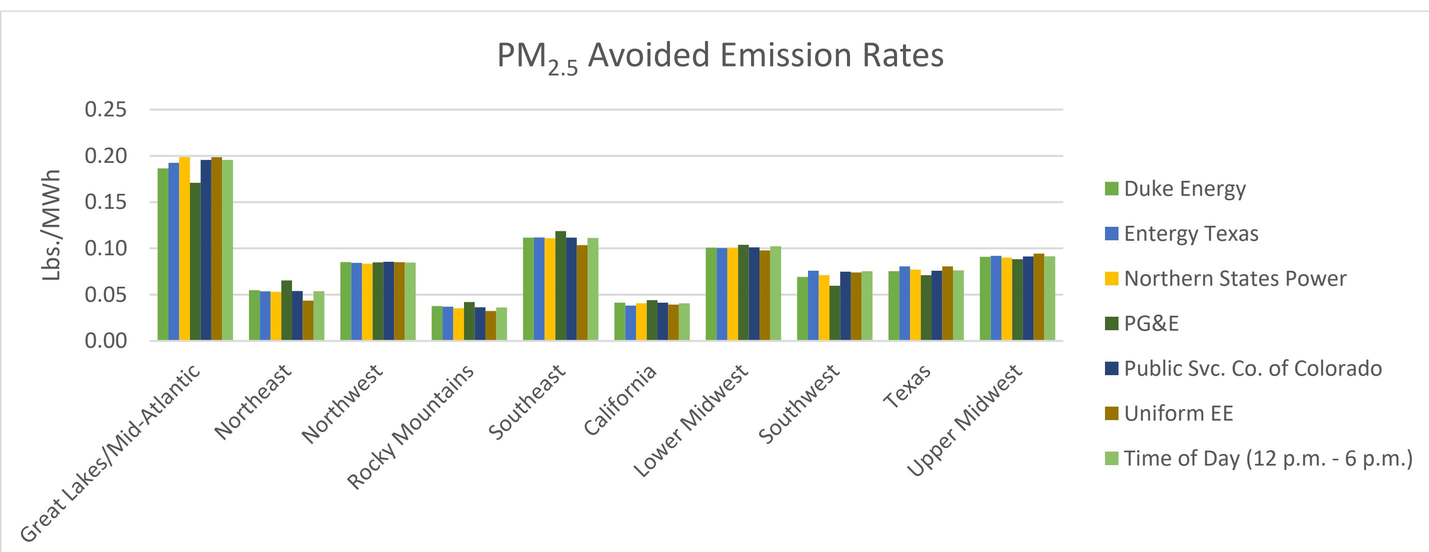


Figure C - 4. Results of Sensitivity Analysis of Definition of Peak Period Based on Different Hours of the Day.

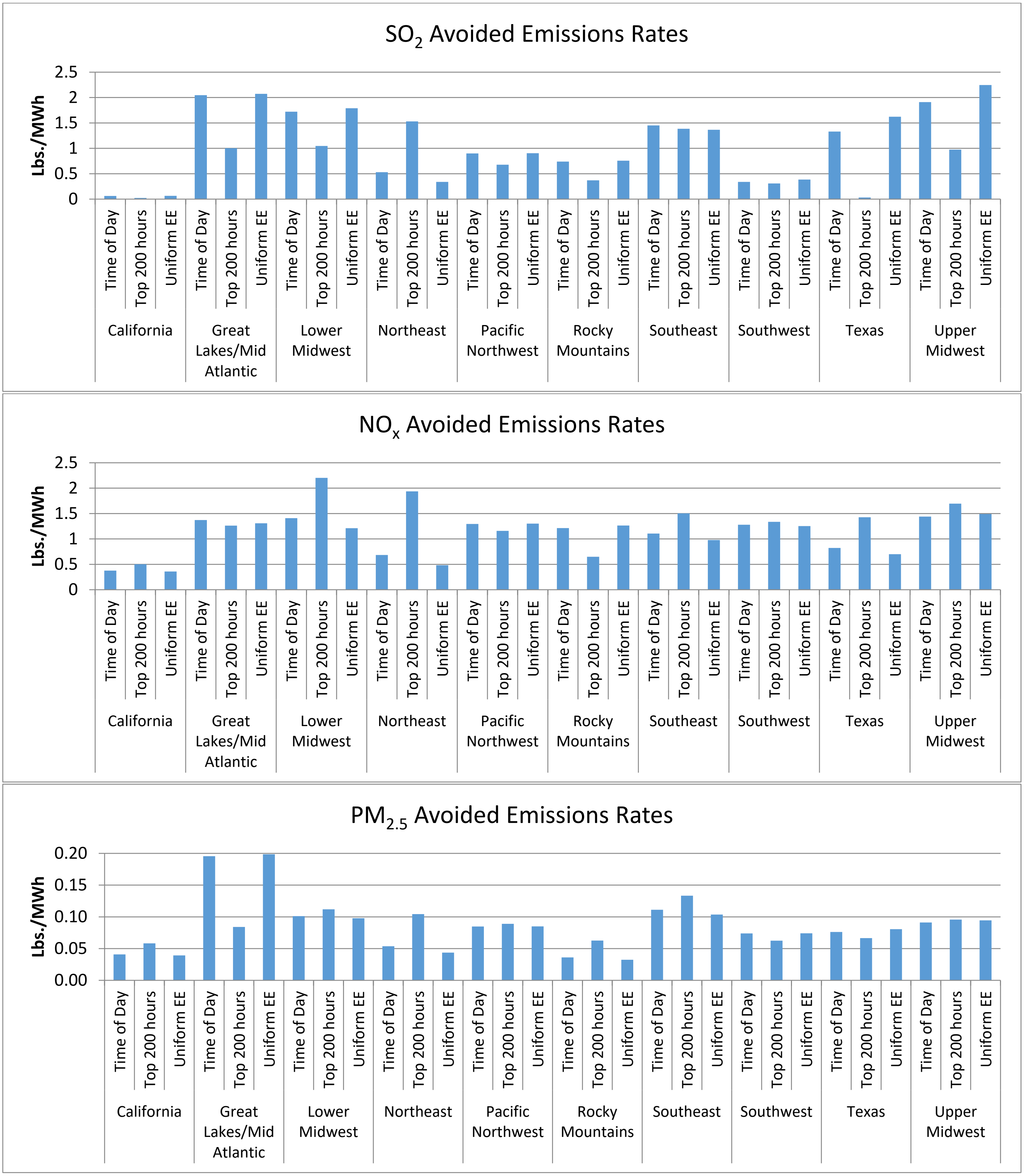


Figure C - 5. Results of Sensitivity Analysis Comparing Emissions Reductions Using Hour-of-Day Approach and Top-Hours-of-Demand Approach to Define the Peak Period.

Appendix D: Top 200 Hours of Demand Benefit-per-kWh Results

Table D - 1 includes the complete modeling results from AVERT and COBRA used to calculate the BPK values for the top 200 hours of demand analysis in each region.

Table D - 1. Complete AVERT and COBRA Results for Top 200 Hours of Demand Analysis (3 percent and 7 percent discount rate; 2017 USD)

Region	Discount Rate	Results from AVERT				SO_2 Emissions Rate (lb./MWh)	NO_X Emissions Rate (lb./MWh)	$PM_{2.5}$ Emissions Rate (lb./MWh)	Results from COBRA		¢/kWh (low)	¢/kWh (high)
		Displaced Generation (MWh)	SO_2 Reduced (lbs.)	NO_X Reduced (lbs.)	$PM_{2.5}$ Reduced (lbs.)				$ Total Health Benefits (low)	$ Total Health Benefits (high)		
California	3	200,230	3,680	33,130	9,530	0.01838	0.16546	0.04760	1,868,183.33	4,221,243.69	0.93	2.11
Great Lakes/Mid-Atlantic	3	205,510	217,960	233,420	35,760	1.06058	1.13581	0.17401	7,353,520.30	16,631,254.33	3.58	8.09
Lower Midwest	3	203,670	3,080	373,040	16,210	0.01512	1.83159	0.07959	1,679,175.59	3,798,562.75	0.82	1.87
Northeast	3	197,440	171,450	210,820	15,640	0.86837	1.06777	0.07921	9,242,207.78	20,874,650.58	4.68	10.57
Pacific Northwest	3	202,330	173,090	228,080	18,200	0.85548	1.12727	0.08995	2,198,711.54	4,972,898.14	1.09	2.46
Rocky Mountains	3	195,720	63,550	226,500	11,870	0.32470	1.15727	0.06065	1,602,727.29	3,625,354.74	0.82	1.85
Southeast	3	201,440	152,400	248,990	24,350	0.75655	1.23605	0.12088	4,045,381.73	9,155,691.94	2.01	4.55
Southwest	3	193,640	7,450	265,600	13,160	0.03847	1.37162	0.06796	1,398,221.15	3,163,872.51	0.72	1.63
Texas	3	197,530	59,330	261,410	13,400	0.30036	1.32339	0.06784	2,243,773.58	5,075,140.16	1.14	2.57
Upper Midwest	3	205,770	133,580	256,210	20,200	0.64917	1.24513	0.09817	3,150,193.28	7,124,723.56	1.53	3.46
California	7	200,230	3,680	33,130	9,530	0.01838	0.16546	0.04760	1,667,429.97	3,765,217.37	0.83	1.88
Great Lakes/Mid-Atlantic	7	205,510	217,960	233,420	35,760	1.06058	1.13581	0.17401	6,561,493.57	14,833,891.17	3.19	7.22
Lower Midwest	7	203,670	3,080	373,040	16,210	0.01512	1.83159	0.07959	1,498,471.30	3,388,096.40	0.74	1.66
Northeast	7	197,440	171,450	210,820	15,640	0.86837	1.06777	0.07921	8,248,584.90	18,620,340.06	4.18	9.43
Pacific Northwest	7	202,330	173,090	228,080	18,200	0.85548	1.12727	0.08995	1,962,089.91	4,435,443.96	0.97	2.19
Rocky Mountains	7	195,720	63,550	226,500	11,870	0.32470	1.15727	0.06065	1,430,318.98	3,233,616.56	0.73	1.65
Southeast	7	201,440	152,400	248,990	24,350	0.75655	1.23605	0.12088	3,609,761.12	8,166,235.14	1.79	4.05
Southwest	7	193,640	7,450	265,600	13,160	0.03847	1.37162	0.06796	1,247,815.35	2,821,961.89	0.64	1.46
Texas	7	197,530	59,330	261,410	13,400	0.30036	1.32339	0.06784	2,002,718.23	4,527,067.37	1.01	2.29
Upper Midwest	7	205,770	133,580	256,210	20,200	0.64917	1.24513	0.09817	2,811,049.78	6,354,838.97	1.37	3.09

Appendix E: Health Impact Functions

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 ambient $PM_{2.5}$ concentrations and adverse human health effects. Table E – 1 summarizes the key values from the epidemiological studies in COBRA used to estimate adverse health impacts of $PM_{2.5}$. The output of each health impact function is the estimated number of incidences of each health outcome given a change in air pollution concentrations.

Total results in COBRA and in this report are reported for a low and high estimate of health impacts, which is a result of multiple C-R functions being used to calculate mortality and nonfatal heart attacks. The high estimate uses the Lepeule et al. (2012) mortality estimate and the Peters et al. (2001) non-fatal heart attack estimates. The low estimate uses the Krewski et al. (2009) mortality estimates and the remaining four acute myocardial infarction estimates. See Appendix C of the COBRA User's Manual for more information.

Table E - 1. Key Health Impact Values in COBRA

Endpoint	Author	Age	Location	Metric	Beta	Standard Error	Functional Form
Mortality, All Cause	Krewski et al. (2009)	30–99	116 U.S. cities	Annual	0.005827	0.000963	Log-linear
Mortality, All Cause	Lepeule et al. (2012)	25–99	6 eastern cities	Annual	0.013103	0.003347	Log-linear
Mortality, All Cause	Woodruff et al. (1997)	Infant	86 cities	Annual	0.003922	0.001221	Logistic
Acute Myocardial Infarction, Nonfatal	Peters et al. (2001)	18–99	Boston, MA	24-hour average	0.024121	0.009285	Logistic
Acute Myocardial Infarction, Nonfatal	Pope et al. (2006)	18–99	Greater Salt Lake City, Utah	24-hour average	0.00481	0.001992	Logistic
Acute Myocardial Infarction, Nonfatal	Sullivan et al. (2005)	18–99	King County, Washington	24-hour average	0.001980	0.002241	Logistic
Acute Myocardial Infarction, Nonfatal	Zanobetti and Schwartz (2006)	18–99	Greater Boston area	24-hour average	0.005300	0.002213	Logistic
Acute Myocardial Infarction, Nonfatal	Zanobetti et al. (2009)	18–99	26 U.S. communities	24-hour average	0.00225	0.000592	Log-linear
Hospital Admissions, All Cardiovascular (less myocardial infarctions)	Bell et al. (2008)	65–99	202 U.S. counties	24-hour average	0.0008	0.00011	Log-linear
Hospital Admissions, All Cardiovascular (less myocardial infarctions)	Moolgavkar (2000b)	18–64	Los Angeles, CA	24-hour average	0.0014	0.00034	Log-linear
Hospital Admissions, All Cardiovascular (less myocardial infarctions)	Peng et al. (2008)	65–99	108 U.S. counties	24-hour average	0.00071	0.00013	Log-linear
Hospital Admissions, All Cardiovascular (less myocardial infarctions)	Peng et al. (2009)	65–99	119 U.S. urban counties	24-hour average	0.00068	0.00021	Log-linear
Hospital Admissions, All Cardiovascular (less myocardial infarctions)	Zanobetti et al. (2009)	65–99	26 U.S. communities	24-hour average	0.00189	0.00028	Log-linear
Hospital Admissions, All Respiratory	Zanobetti et al. (2009)	65–99	26 U.S. communities	24-hour average	0.00207	0.00045	Log-linear

Endpoint	Author	Age	Location	Metric	Beta	Standard Error	Functional Form
Hospital Admissions, All Respiratory	Kloog et al. (2012)	65–99	New England area (6 states)	24-hour average	0.0007	0.00096	Log-linear
Hospital Admissions, Asthma	Babin et al. (2007)	0–17	Washington, DC	24-hour average	0.002	0.00434	Log-linear
Hospital Admissions, Asthma	Sheppard (2003)	0–17	Seattle, WA	24-hour average	0.00332	0.00104	Log-linear
Hospital Admissions, Chronic Lung Disease	Moolgavkar (2000a)	18–64	Los Angeles, CA	24-hour average	0.0022	0.00073	Log-linear
Emergency Room Visits, Asthma	Mar et al. (2010)	0–99	Greater Tacoma, Washington	24-hour average	0.0056	0.0021	Log-linear
Emergency Room Visits, Asthma	Slaughter et al. (2005)	0–99	Spokane, Washington	24-hour average	0.0029	0.0027	Log-linear
Emergency Room Visits, Asthma	Glad et al. (2012)	0–99	Pittsburgh, PA	24-hour average	0.0039	0.0028	Logistic
Acute Bronchitis	Dockery et al. (1996)	8–12	24 communities	Annual	0.027212	0.017096	Logistic
Asthma Exacerbation, Cough	Mar et al. (2004)	6–18	Vancouver, CAN	24-hour average	0.01906	0.009828	Logistic
Asthma Exacerbation, Cough	Ostro et al. (2001)	6–18	Los Angeles, CA	24-hour average	0.000985	0.000747	Logistic
Asthma Exacerbation, Shortness of Breath	Mar et al. (2004)	6–18	Vancouver, CAN	24-hour average	0.01222	0.013849	Logistic
Asthma Exacerbation, Shortness of Breath	Ostro et al. (2001)	6–18	Los Angeles, CA	24-hour average	0.002565	0.001335	Logistic
Asthma Exacerbation, Wheeze	Ostro et al. (2001)	6–18	Los Angeles, CA	24-hour average	0.001942	0.000803	Logistic
Minor Restricted Activity Days	Ostro and Rothschild (1989)	18–64	Nationwide	24-hour average	0.007410	0.000700	Log-linear
Lower Respiratory Symptoms	Schwartz and Neas (2000)	7–14	6 U.S. cities	24-hour average	0.019012	0.006005	Logistic
Upper Respiratory Symptoms	Pope et al. (1991)	9–11	Utah Valley	24-hour average	0.0036	0.0015	Logistic
Work Loss Days	Ostro (1987)	18–64	Nationwide	24-hour average	0.004600	0.000360	Log-linear

Appendix F: Health Benefits Valuation

Table F – 1 presents the mean estimate of the unit values used in COBRA to estimate the monetary value of the health effects. The unit values are based on published estimates of the costs of treating the illness (which can include both direct medical costs and costs of lost productivity), or the willingness-to-pay (WTP) to avoid the illness or to reduce the risk of premature death (i.e., VSL). The unit values based on WTP estimates reflect the 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. See Appendix F of the COBRA User's Manual for more information.

Table F - 1. COBRA Value of Health Effects

Health Endpoint	Age Range	Unit Value (2017 USD at the 2017 income level)	
		3% Discount Rate	7% Discount Rate
Mortality[a]	25–99	$9,447,115	$8,414,395
Infant Mortality[b]	0–0	$10,529,882	$10,529,882
Acute Myocardial Infarction, Nonfatal[c]	0–24	$37,250	$35,220
Acute Myocardial Infarction, Nonfatal[c]	25–44	$50,495	$47,077
Acute Myocardial Infarction, Nonfatal[c]	45–54	$56,772	$52,696
Acute Myocardial Infarction, Nonfatal[c]	55–64	$150,083	$136,238
Acute Myocardial Infarction, Nonfatal[c]	65–99	$37,250	$35,220
Acute Myocardial Infarction, Nonfatal[d]	0–24	$182,617	$182,617
Acute Myocardial Infarction, Nonfatal[d]	25–44	$195,861	$194,475
Acute Myocardial Infarction, Nonfatal[d]	45–54	$202,138	$200,094
Acute Myocardial Infarction, Nonfatal[d]	55–64	$295,450	$283,637
Acute Myocardial Infarction, Nonfatal[d]	65–99	$182,617	$182,617
Hospital Admissions, All Cardiovascular (less-acute myocardinal infraction)	18–64	$45,922	$45,922
Hospital Admissions, All Cardiovascular (less-acute myocardinal infraction)	65–99	$43,252	$43,252
Hospital Admissions, All Respiratory	65–99	$36,621	$36,621
Hospital Admissions, Asthma	0–17	$17,282	$17,282
Hospital Admissions, Chronic Lung Disease	18–64	$22,791	$22,791
Asthma Emergency Room Visits (Smith et al. 1997)	0–99	$520	$520
Asthma Emergency Room Visits (Stanford et al. 1999)	0–99	$435	$435
Acute Bronchitis	8–12	$534	$534
Lower Respiratory Symptoms	7–14	$24	$24
Upper Respiratory Symptoms	9–11	$37	$37
Minor Restricted Activity Days	18–64	$76	$76
Work Loss Days	18–64	$179	$179
Asthma Exacerbation (cough, shortness of breath, or wheeze)	6–18	$64	$64

[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).

Appendix G: Detailed Benefits-per-kWh Results

Table G – 1 includes the complete modeling results from AVERT and COBRA used to calculate the BPK values for each region and technology type.

Table G - 1. Complete AVERT and COBRA Results for 2017 (3 percent and 7 percent discount rate; 2017 USD)

Region	Project Type	Discount Rate	Results from AVERT				SO_2 Emissions Rate (lb./MWh)	NO_x Emissions Rate (lb./MWh)	PM_{25} Emissions Rate (lb./MWh)	Results from COBRA		¢/kWh (low)	¢/kWh (high)
			Displaced Generation (MWh)	SO_2 Reduced (lbs.)	NO_x Reduced (lbs.)	PM_{25} Reduced (lbs.)				$ Total Health Benefits (low)	$ Total Health Benefits (high)		
California	Uniform EE	3	522,060	37,410	165,980	23,090	0.07166	0.31793	0.04423	2,484,934	5,617,248	0.48	1.08
	EE at Peak	3	200,130	13,110	57,400	8,620	0.06551	0.28681	0.04307	1,036,707	2,343,226	0.52	1.17
	Solar	3	194,380	13,780	62,970	8,940	0.07089	0.32395	0.04599	990,413	2,238,698	0.51	1.15
	Wind	3	151,660	11,150	49,200	6,720	0.07352	0.32441	0.04431	727,998	1,645,588	0.48	1.09
Great Lakes/ Mid-Atlantic	Uniform EE	3	521,980	606,820	478,260	102,050	1.16253	0.91624	0.19551	18,347,102	41,496,455	3.51	7.95
	EE at Peak	3	198,470	228,410	192,760	38,100	1.15085	0.97123	0.19197	7,094,665	16,046,296	3.57	8.08
	Solar	3	153,580	184,740	144,290	30,320	1.20289	0.93951	0.19742	5,629,211	12,731,861	3.67	8.29
	Wind	3	226,120	243,150	210,750	44,120	1.07531	0.93203	0.19512	7,585,426	17,156,015	3.35	7.59
Lower Midwest	Uniform EE	3	526,240	919,370	588,070	48,430	1.74705	1.11749	0.09203	12,162,120	27,515,418	2.31	5.23
	EE at Peak	3	199,500	305,300	239,080	18,030	1.53033	1.19840	0.09038	4,204,249	9,511,507	2.11	4.77
	Solar	3	188,940	303,910	220,330	17,280	1.60850	1.16614	0.09146	4,140,826	9,368,042	2.19	4.96
	Wind	3	352,100	632,180	386,340	32,440	1.79546	1.09725	0.09213	8,272,975	18,716,683	2.35	5.32
Northeast	Uniform EE	3	528,750	138,810	212,330	22,240	0.26252	0.40157	0.04206	8,736,861	19,732,529	1.65	3.73
	EE at Peak	3	200,980	73,510	103,110	9,900	0.36576	0.51304	0.04926	4,510,929	10,187,690	2.24	5.07
	Solar	3	157,560	47,320	73,000	7,260	0.30033	0.46332	0.04608	3,056,040	6,901,902	1.94	4.38
	Wind	3	175,560	47,150	64,520	7,090	0.26857	0.36751	0.04039	2,769,336	6,254,873	1.58	3.56
Pacific Northwest	Uniform EE	3	520,420	441,810	620,760	41,960	0.84895	1.19281	0.08063	5,874,146	13,285,524	1.13	2.55
	EE at Peak	3	199,410	170,770	237,720	16,510	0.85638	1.19212	0.08279	2,242,063	5,070,811	1.12	2.54
	Solar	3	173,790	150,810	212,850	14,230	0.86777	1.22475	0.08188	2,028,039	4,586,878	1.17	2.64
	Wind	3	220,430	183,720	261,500	17,740	0.83346	1.18632	0.08048	2,483,003	5,615,855	1.13	2.55

Region	Project Type	Discount Rate	Results from AVERT: Displaced Generation (MWh)	Results from AVERT: SO_2 Reduced (lbs.)	Results from AVERT: NO_x Reduced (lbs.)	Results from AVERT: PM_{25} Reduced (lbs.)	SO_2 Emissions Rate (lb./MWh)	NO_x Emissions Rate (lb./MWh)	PM_{25} Emissions Rate (lb./MWh)	Results from COBRA: $ Total Health Benefits (low)	Results from COBRA: $ Total Health Benefits (high)	¢/kWh (low)	¢/kWh (high)
Rocky Mountains	Uniform EE	3	521,840	288,080	687,930	17,370	0.55205	1.31828	0.03329	5,359,681	12,124,457	1.03	2.32
	EE at Peak	3	199,330	102,310	244,880	7,340	0.51327	1.22852	0.03682	1,951,438	4,414,401	0.98	2.21
	Solar	3	197,300	101,990	251,560	6,950	0.51693	1.27501	0.03523	1,961,721	4,437,674	0.99	2.25
	Wind	3	306,950	176,630	412,520	9,920	0.57544	1.34393	0.03232	3,274,588	7,407,658	1.07	2.41
Southeast	Uniform EE	3	524,860	386,360	455,140	50,980	0.73612	0.86716	0.09713	9,319,089	21,094,677	1.78	4.02
	EE at Peak	3	199,380	151,520	201,430	20,870	0.75996	1.01028	0.10467	3,733,770	8,451,618	1.87	4.24
	Solar	3	168,790	126,600	160,410	17,150	0.75004	0.95035	0.10161	3,097,209	7,010,795	1.83	4.15
	Wind	3	120,130	88,370	99,640	11,330	0.73562	0.82943	0.09431	2,110,045	4,776,336	1.76	3.98
Southwest	Uniform EE	3	521,270	122,320	472,260	36,220	0.23466	0.90598	0.06948	3,726,818	8,432,593	0.71	1.62
	EE at Peak	3	200,550	38,430	194,520	13,990	0.19162	0.96993	0.06976	1,408,299	3,186,512	0.70	1.59
	Solar	3	226,200	51,830	211,860	16,040	0.22913	0.93660	0.07091	1,640,241	3,711,328	0.73	1.64
	Wind	3	213,890	61,000	192,250	15,530	0.28519	0.89883	0.07261	1,636,309	3,702,391	0.77	1.73
Texas	Uniform EE	3	526,050	655,200	324,990	37,900	1.24551	0.61779	0.07205	8,317,315	18,817,958	1.58	3.58
	EE at Peak	3	199,800	198,090	137,810	13,420	0.99144	0.68974	0.06717	2,767,366	6,260,993	1.39	3.13
	Solar	3	182,460	191,100	120,880	12,360	1.04735	0.66250	0.06774	2,593,074	5,866,753	1.42	3.22
	Wind	3	295,870	387,990	176,990	21,620	1.31135	0.59820	0.07307	4,823,340	10,912,883	1.63	3.69
Upper Midwest	Uniform EE	3	524,750	991,470	675,020	48,130	1.88941	1.28636	0.09172	16,377,183	37,044,470	3.12	7.06
	EE at Peak	3	199,200	316,380	248,570	17,600	1.58825	1.24784	0.08835	5,475,798	12,385,741	2.75	6.22
	Solar	3	167,860	283,770	207,880	14,960	1.69052	1.23841	0.08912	4,848,718	10,967,473	2.89	6.53
	Wind	3	360,360	699,550	471,900	33,180	1.94125	1.30952	0.09207	11,521,813	26,061,951	3.20	7.23
California	Uniform EE	7	522,060	37,410	165,980	23,090	0.07166	0.31793	0.04423	2,217,845	5,010,362	0.42	0.96
	EE at Peak	7	200,130	13,110	57,400	8,620	0.06551	0.28681	0.04307	925,286	2,090,072	0.46	1.04
	Solar	7	194,380	13,780	62,970	8,940	0.07089	0.32395	0.04599	883,962	1,996,832	0.45	1.03
	Wind	7	151,660	11,150	49,200	6,720	0.07352	0.32441	0.04431	649,750	1,467,800	0.43	0.97
Great Lakes/ Mid-Atlantic	Uniform EE	7	521,980	606,820	478,260	102,050	1.16253	0.91624	0.19551	16,370,600	37,011,474	3.14	7.09
	EE at Peak	7	198,470	228,410	192,760	38,100	1.15085	0.97123	0.19197	6,330,389	14,312,011	3.19	7.21
	Solar	7	153,580	184,740	144,290	30,320	1.20289	0.93951	0.19742	5,022,792	11,355,790	3.27	7.39
	Wind	7	226,120	243,150	210,750	44,120	1.07531	0.93203	0.19512	6,768,256	15,301,768	2.99	6.77
Lower Midwest	Uniform EE	7	526,240	919,370	588,070	48,430	1.74705	1.11749	0.09203	10,852,982	24,542,104	2.06	4.66
	EE at Peak	7	199,500	305,300	239,080	18,030	1.53033	1.19840	0.09038	3,751,710	8,483,698	1.88	4.25
	Solar	7	188,940	303,910	220,330	17,280	1.60850	1.16614	0.09146	3,695,110	8,355,735	1.96	4.42
	Wind	7	352,100	632,180	386,340	32,440	1.79546	1.09725	0.09213	7,382,465	16,694,159	2.10	4.74
Northeast	Uniform EE	7	528,750	138,810	212,330	22,240	0.26252	0.40157	0.04206	7,796,956	17,601,071	1.47	3.33
	EE at Peak	7	200,980	73,510	103,110	9,900	0.36576	0.51304	0.04926	4,025,772	9,087,337	2.00	4.52
	Solar	7	157,560	47,320	73,000	7,260	0.30033	0.46332	0.04608	2,727,332	6,156,418	1.73	3.91
	Wind	7	175,560	47,150	64,520	7,090	0.26857	0.36751	0.04039	2,471,374	5,579,212	1.41	3.18

Region	Project Type	Discount Rate	Results from AVERT				SO_2 Emissions Rate (lb./MWh)	NO_x Emissions Rate (lb./MWh)	PM_{25} Emissions Rate (lb./MWh)	Results from COBRA		¢/kWh (low)	¢/kWh (high)
			Displaced Generation (MWh)	SO_2 Reduced (lbs.)	NO_x Reduced (lbs.)	PM_{25} Reduced (lbs.)				$ Total Health Benefits (low)	$ Total Health Benefits (high)		
Pacific Northwest	Uniform EE	7	520,420	441,810	620,760	41,960	0.84895	1.19281	0.08063	5,241,959	11,849,667	1.01	2.28
	EE at Peak	7	199,410	170,770	237,720	16,510	0.85638	1.19212	0.08279	2,000,768	4,522,771	1.00	2.27
	Solar	7	173,790	150,810	212,850	14,230	0.86777	1.22475	0.08188	1,809,784	4,091,150	1.04	2.35
	Wind	7	220,430	183,720	261,500	17,740	0.83346	1.18632	0.08048	2,215,783	5,008,918	1.01	2.27
Rocky Mountains	Uniform EE	7	521,840	288,080	687,930	17,370	0.55205	1.31828	0.03329	4,783,050	10,814,286	0.92	2.07
	EE at Peak	7	199,330	102,310	244,880	7,340	0.51327	1.22852	0.03682	1,741,497	3,937,384	0.87	1.98
	Solar	7	197,300	101,990	251,560	6,950	0.51693	1.27501	0.03523	1,750,671	3,958,141	0.89	2.01
	Wind	7	306,950	176,630	412,520	9,920	0.57544	1.34393	0.03232	2,922,287	6,607,187	0.95	2.15
Southeast	Uniform EE	7	524,860	386,360	455,140	50,980	0.73612	0.86716	0.09713	8,315,459	18,814,863	1.58	3.58
	EE at Peak	7	199,380	151,520	201,430	20,870	0.75996	1.01028	0.10467	3,331,679	7,538,222	1.67	3.78
	Solar	7	168,790	126,600	160,410	17,150	0.75004	0.95035	0.10161	2,763,662	6,253,109	1.64	3.70
	Wind	7	120,130	88,370	99,640	11,330	0.73562	0.82943	0.09431	1,882,797	4,260,129	1.57	3.55
Southwest	Uniform EE	7	521,270	122,320	472,260	36,220	0.23466	0.90598	0.06948	3,325,818	7,521,287	0.64	1.44
	EE at Peak	7	200,550	38,430	194,520	13,990	0.19162	0.96993	0.06976	1,256,774	2,842,148	0.63	1.42
	Solar	7	226,200	51,830	211,860	16,040	0.22913	0.93660	0.07091	1,463,756	3,310,247	0.65	1.46
	Wind	7	213,890	61,000	192,250	15,530	0.28519	0.89883	0.07261	1,460,238	3,302,273	0.68	1.54
Texas	Uniform EE	7	526,050	655,200	324,990	37,900	1.24551	0.61779	0.07205	7,423,071	16,785,407	1.41	3.19
	EE at Peak	7	199,800	198,090	137,810	13,420	0.99144	0.68974	0.06717	2,469,838	5,584,731	1.24	2.80
	Solar	7	182,460	191,100	120,880	12,360	1.04735	0.66250	0.06774	2,314,285	5,233,080	1.27	2.87
	Wind	7	295,870	387,990	176,990	21,620	1.31135	0.59820	0.07307	4,304,745	9,734,164	1.45	3.29
Upper Midwest	Uniform EE	7	524,750	991,470	675,020	48,130	1.88941	1.28636	0.09172	14,613,805	33,041,446	2.78	6.30
	EE at Peak	7	199,200	316,380	248,570	17,600	1.58825	1.24784	0.08835	4,886,201	11,047,331	2.45	5.55
	Solar	7	167,860	283,770	207,880	14,960	1.69052	1.23841	0.08912	4,326,639	9,782,324	2.58	5.83
	Wind	7	360,360	699,550	471,900	33,180	1.94125	1.30952	0.09207	10,281,224	23,245,697	2.85	6.45

Appendix H: Conversions

Table H – 1 lists common conversions used throughout this report.

Table H - 1. Common Conversions.

Original Units	Multiply by	To Obtain
¢/kWh	1,000	¢/MWh
¢/kWh	1,000,000	¢/GWh

U.S. Environmental Protection Agency
State and Local Energy and Environment Program
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