

# Estimating PM<sub>2.5</sub>- and Ozone-Attributable Health Benefits: 2024 Update

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## PREFACE

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In March of 2021, EPA published a version of this Technical Support Document (TSD) titled “Estimating PM<sub>2.5</sub>- and Ozone-Attributable Health Benefits” ((U.S. EPA 2021)). That original TSD drew upon evidence published in the Integrated Science Assessments (ISA) for PM<sub>2.5</sub> and ozone available at that point in time ((U.S. EPA 2019, U.S. EPA 2020)). EPA recently published a Supplement to the PM ISA ((U.S. EPA 2022)). This updated version of the TSD evaluates this new evidence and identifies alternative epidemiologic studies and risk estimates to support EPA benefits analyses.

EPA expects to revise this TSD as new health, demographic, and economic evidence becomes available. The table below summarizes the: (1) version and publication date of each TSD; (2) reason for updating the TSD; (3) key changes as compared to the prior version. Each version of the TSD may be found on the EPA website at: [www.epa.gov/benmap](http://www.epa.gov/benmap).

Version Date	Update Rationale	Key Changes
March 2021	Describe benefits methods updated in response to the 2019 PM ISA and used to support the Revised Cross-State Air Pollution Update Regulatory Impact Analysis	NA
December 2022	Describe benefits methods updated in response to the 2022 Supplement to the PM ISA and used to support the Regulatory Impact Analysis for the Proposed Reconsideration of the PM NAAQS	<ul style="list-style-type: none"> <li>Revised risk estimates used to quantify PM<sub>2.5</sub>-related mortality and non-fatal heart attacks</li> <li>Updated school loss day valuation estimate</li> <li>Updated discussion of uncertainty associated with PM<sub>2.5</sub>-related premature mortality</li> </ul>
June 2024	Updates in response to Circular A-4 and SAB guidance.	<ul style="list-style-type: none"> <li>Added valuation estimates based on a 2% Discount Rate</li> <li>Updated criteria for identifying studies and risk estimates to include studies published since the most recent ISA or equivalent and to include studies published outside the U.S. and Canada</li> </ul>



# 1 INTRODUCTION

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## 1.1 BENEFITS ANALYSIS BACKGROUND

The EPA's *Guidelines for Preparing Economic Analyses* describe the purpose of benefit-cost analysis (BCA), related economic analyses, and the best-practices for conducting them ((U.S. EPA 2014)). BCA is the primary tool used for regulatory analysis and is used to inform the decision of whether the benefits of an action are likely to justify the costs ((Exec. Order No. 12898 1994), (OMB 2003)). As described in the *Guidelines*, the fundamental objective of a BCA is to determine whether those who experience a net gain from a regulatory action can potentially compensate those who experience a net loss and remain no worse off. These gains and losses are measured by an individual's willingness to pay (WTP) for, or willingness to accept, changes attributable to the regulatory action. Consistent with economic theory, the WTP for reducing an exposure to an environmental hazard, like PM<sub>2.5</sub> or O<sub>3</sub>, depends on the expected effect of those reductions on human health.

Estimating the health benefits of reducing PM<sub>2.5</sub> and O<sub>3</sub> exposure in a BCA begins with estimating the population-level change in exposure and then estimating the population-level change in risk for those health outcomes affected by exposure. The benefit of reducing these health risks is estimated using a summary measure of the population-level WTP for the risk change.<sup>1</sup> The greater the magnitude of the risk reduction from a given change in concentration, the greater the WTP, all else equal. The social benefit of the change in health risks equals the sum of the individual WTP estimates across all of the affected individuals.<sup>2</sup> There are various sources of uncertainty inherent in each of these steps, many of which are discussed in section 6.

There are three key information collection and assessment steps for implementing this framework for evaluating the health benefits of changes in exposure:

- (1) Identifying health endpoints affected by exposure by assessing the strength of evidence,
- (2) Identifying suitable empirical estimates of the magnitude of the relationship between exposure and these health endpoints, and
- (3) Estimating the WTP for reductions in the risk of these health endpoints.

This document describes all three steps for the purposes of estimating health benefits from changes in ambient PM<sub>2.5</sub> and O<sub>3</sub> exposure.<sup>3</sup>

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<sup>1</sup> As described in section 0, cost-of-illness (COI) estimates are used as a proxy for WTP estimates due to data limitations.

<sup>2</sup> BCA also often report the change in the sum of the risk, or the change in the total incidence, of a health outcome across the population. If WTP per unit of risk is invariant across individuals, the total expected change in the incidence of the health outcome across the population can be multiplied by the WTP per unit of risk to estimate the social benefit of the total expected change in the incidence of the health outcome. Also, if suitable WTP estimates for a health effect are unavailable, this effect will still, when possible, be quantified to provide a full picture of the potential benefits of a regulation.

<sup>3</sup> In addition to EPA's *Guidelines for Preparing Economic Analyses*, these methods and choices adhere to other relevant EPA and OMB guidance documents, EPA regulations, previous scientific advisory reviews, and available

## 1.2 THE RELATIONSHIP BETWEEN IDENTIFYING HEALTH ENDPOINTS FOR VALUATION AND WTP

The first step requires collecting and integrating scientific evidence from different types of studies and scientific fields (e.g., epidemiologic, controlled human exposure, and animal toxicological studies), as well as evaluating the quality of evidence and the consistency in the pattern of effects. Determining the strengths, limitations, and uncertainties in the overall evidence are key components, all of which could affect WTP, as this information is the basis of the desire to avoid or reduce PM<sub>2.5</sub> and O<sub>3</sub> exposure.

While the first and third step are presented as independent, they are related for an individual. All else equal, WTP is expected to be higher when there is stronger evidence of a causal relationship between exposure to the contaminant and changes in a health outcome ((McGartland, Revesz et al. 2017)).<sup>4,5</sup> For example, in the case where there is no evidence of a potential relationship the WTP would be expected to be zero and the effect should be excluded from the analysis. Alternatively, when there is some evidence of a relationship between exposure and the health outcome, but that evidence is insufficient to definitively conclude that there is a causal relationship, individuals may have a positive WTP for a reduction in exposure to that hazard ((Kivi and Shogren 2010, Honeycutt 2020)). Lastly, the WTP for reductions in exposure to pollutants with strong evidence of a relationship between exposure and effect are likely positive and larger than for endpoints where evidence is weak, all else equal. Unfortunately, the economic literature currently lacks a settled approach for accounting for how WTP may vary with uncertainty about causal relationships.

Given these challenges, for step 1 the EPA draws its assessment of the strength of evidence on the relationship between exposure to PM<sub>2.5</sub> or O<sub>3</sub> and potential health endpoints from the Integrated Science Assessments (ISAs) that are developed for the NAAQS process. Specifically, in the PM<sub>2.5</sub> and O<sub>3</sub> benefits analysis for the Regulatory Impact Analysis for the Proposed Reconsideration of the PM NAAQS, the EPA quantifies and monetizes all health effects that the ISA draws conclusions regarding the causal relationship between a pollutant and a given effect, noting whether the effect is “causal” or “likely to be causal,” following scientific assessment methods described in the ISAs. The focus on categories identified as having a “causal” or “likely to be causal” relationship with the pollutant of interest is to estimate the pollutant-attributable human health benefits in which we are most confident.<sup>6</sup> All else equal, this approach may underestimate the benefits of PM<sub>2.5</sub> and O<sub>3</sub> exposure reductions as individuals may be WTP to avoid specific risks where the evidence is insufficient to conclude they are “likely to be

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scientific information (U.S. EPA (2014). Guidelines for Preparing Economic Analyses, National Center for Environmental Economics. US Environmental Protection Agency Washington, DC.).

<sup>4</sup> It is also case that the third step depends on sources of uncertainty in the second step. That is, even if a causal relationship between exposure and a particular health risk were established with certainty, the precise empirical relationship between exposure and effect may not be known, and of the resulting uncertainty may influence the WTP to avoid this risk. For example, there may be parameter or model uncertainty in the empirical relationship between exposure and a health effect that would influence the WTP to avoid exposure (Freeman III, A. M., J. A. Herriges and C. L. Kling (2014). The measurement of environmental and resource values: theory and methods, Routledge.). Section 5 describes how WTP estimates may be influenced by these sources of uncertainty.

<sup>5</sup> Here we are referring to causality as a general notion of how well established the relationship between a cause and possible effect is for the purposes of estimating WTP, and not to the specific approach for evaluating and determining causality between health effects and PM<sub>2.5</sub> and O<sub>3</sub> exposure used in the ISAs.

<sup>6</sup> This decision criterion for selecting health effects to quantify and monetize PM<sub>2.5</sub> and O<sub>3</sub> is only applicable to estimating the benefits of exposure of these two pollutants. This decision criterion may not be applicable or suitable for quantifying and monetizing health and ecological effects of other pollutants.

caus[ed]” by exposure to these pollutants.<sup>7</sup> At the same time, WTP may be lower for those health outcomes for which causality has not been definitively established. This approach treats relationships with ISA causality determinations of “likely to be causal” as if they are known to be causal, and therefore benefits could be overestimated (section 6.5.2). This approach may be revisited in the future with scientific advancements and development of a theoretically consistent framework that jointly accounts for causal uncertainty and individuals’ WTP for reducing uncertain health impacts.

### 1.3 DOCUMENT PURPOSE AND OVERVIEW

This is a technical support document (TSD) to the Proposed Particulate Matter National Ambient Air Quality Standards (hereafter, PM NAAQS). This document is organized according to the three key steps we follow to collect information the information needed to quantify and monetize benefits, as presented in section 1.1:

1. Establish criteria for identifying studies and risk estimates most appropriate to inform a PM<sub>2.5</sub> and O<sub>3</sub> benefit analysis for an RIA (section 2.1). Study criteria, such as study design, location, population characteristics, and other attributes, were used to identify the most suitable estimates.<sup>8</sup> Establishing these criteria prior to selecting candidate health endpoints helps reduce the chance of bias in the process for selecting endpoints.
2. Identify pollutant-attributable health effects for which the ISA reports strong evidence and that may be quantified in a benefits assessment (section 2.2). Each ISA identifies some number of clinically significant air pollution-related outcomes (e.g., premature mortality and hospital admissions) ((U.S. EPA 2019, U.S. EPA 2020)) that may be quantified and possibly also monetized. Each selected endpoint and study must meet the criteria specified in section 2.1 above.
3. Collect baseline incidence and prevalence estimates (section 3) and demographic information (section 4). EPA uses health impact functions to quantify counts of pollutant-attributable effects. These functions uses population and rates of death and disease. EPA selected either daily or annual baseline incidence and prevalence rates at the most geographically- and age-specific levels feasible for each health endpoint assessed. Projected population counts are drawn from the Woods and Poole, Inc. ((Woods & Poole 2015)). The Woods and Poole (WP) database contains county-level projections of population by age, sex, and race out to 2050, relative to a baseline using the 2010 Census data.
4. Develop economic unit values (section 5). To compare benefits estimates associated with a rulemaking directly with the estimated cost, counts of each air pollution-attributable event must

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<sup>7</sup> EPA includes an example health endpoint with a causality determination of “suggestive, but not sufficient to infer” and associated with a potentially substantial economic value in the quantitative uncertainty characterization (section 6.2.3).

<sup>8</sup> If recent ISAs identify more new epidemiologic studies that are better suited than the prior studies for estimating risks for endpoints whose causality did not change between the prior ISA and the current ISA (e.g., respiratory hospital admissions), we use this new epidemiologic evidence to estimate risks despite the causality conclusion not changing between the prior and most recent ISAs.

be expressed as an economic value. This step requires us to estimate a single year or multi-year stream of discounted values for each unique health endpoint.

5. Characterize uncertainty associated with quantified benefits estimates (section 6). Building on EPA's current methods for characterizing uncertainty, these approaches include, among others, reporting confidence intervals calculated from risk estimates, separate quantification using multiple studies and risk estimates for particularly influential endpoints (e.g., mortality risk), and approaches for aggregating and representing the results of multiple studies evaluating a particular health endpoint.<sup>9</sup>

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<sup>9</sup> Study quality, inter-study heterogeneity, and redundancy issues will be taken into consideration if epidemiologic risk estimates are aggregated.

## 2 APPROACH TO IDENTIFYING STUDIES AND RISK ESTIMATES<sup>10</sup>

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This section describes the criteria EPA developed when selecting among fine particulate matter (PM<sub>2.5</sub>) and ozone (O<sub>3</sub>) epidemiologic studies and risk estimates to quantify air pollution-attributable health impacts for regulatory purposes, such as Regulatory Impact Analyses (RIAs). We specify the criteria used to identify the available body of epidemiologic literature potentially suitable for supporting a benefits analysis (section 2.2); apply the identification criteria to the body of available literature (section 2.3); and, finally, present the identified health endpoints and risk estimates (section 2.4) that best characterize risk to the U.S. population for health impact benefits assessments. The identification criteria precede the health endpoint identification because epidemiologic studies must meet certain minimum criteria (section 2.1.1).

### 2.1 STUDY AND RISK ESTIMATE IDENTIFICATION CRITERIA

We follow a systematic approach to identify the studies and risk estimates most appropriate to inform a PM<sub>2.5</sub> and O<sub>3</sub> benefit analysis for an RIA.<sup>11</sup> Epidemiologic studies report estimated risks of population exposure to one or more pollutants across a variety of geographic locations, age groups, population attributes, methods for estimating exposure, PM<sub>2.5</sub> and O<sub>3</sub> concentrations, time periods, study sizes, follow-up durations, and other attributes. Clearly specifying criteria for identifying such studies helps ensure EPA transparently specifies its scientific judgement. These criteria are similar to those applied in previous EPA RIAs (Table 1) with the primary goal of identifying risk estimates that best characterize risk from PM<sub>2.5</sub> and O<sub>3</sub> exposure among the total population located throughout the U.S.<sup>12</sup>

#### 2.1.1 Minimum Criteria

All studies must meet the following minimum required criteria to be considered for use in PM<sub>2.5</sub> and O<sub>3</sub> benefits assessments. These minimum criteria ensure that the subset of studies evaluated include the information necessary to justifiably quantify health effects when estimating benefits across the U.S.

1. The study must be referenced in the latest externally reviewed ISA or equivalent assessment (e.g., provisional assessment or supplement) to ensure the literature search and screening process were performed in a transparent and systematic manner and only included peer-reviewed research, or have been published since the latest externally reviewed ISA or equivalent assessment and represent an improvement upon the scientific literature at the time of the latest externally reviewed ISA or equivalent assessment.

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<sup>10</sup> What we call risk estimates in this document are results from epidemiologic studies characterizing the magnitude of exposure-related risk. This term is synonymous with several others, including concentration-response functions, effect estimates, health impact functions, risk models, and beta ( $\beta$ ) coefficients.

<sup>11</sup> Epidemiological studies estimate the association between exposure to air pollution concentrations and adverse health outcomes and generally provide a relative comparison about the strength of the relationship between exposure to air pollution and the health outcome, rather than estimating the absolute health impact of an exposure (i.e., the number of avoided cases). For example, a 10  $\mu\text{g}/\text{m}^3$  decrease in daily PM<sub>2.5</sub> levels might be associated with a decrease in hospital admissions of 5% or a 5 ppb decrease in 8-hour maximum daily ozone concentration might be associated with a decrease in hospital admissions of 3%. A benefits analysis reports absolute values with respect to the public health impact of an exposure.

<sup>12</sup> See: [https://www3.epa.gov/ttn/ecas/docs/ria/naaq5-pm\\_ria\\_final\\_2012-12.pdf](https://www3.epa.gov/ttn/ecas/docs/ria/naaq5-pm_ria_final_2012-12.pdf)

2. The study must have been epidemiologic in nature, assess either PM<sub>2.5</sub> or O<sub>3</sub>, and report numerical risks/hazards expressed as per a unit change in pollutant concentration (and an accompanying estimated standard error) to provide the information needed to quantify mean estimates of effects and 95% confidence intervals.

### 2.1.2 Preferred Criteria Categories

Studies meeting the minimum criteria are then evaluated based on various factors, which we call preferred criteria, to identify risk estimates that best characterize air pollution risk across the U.S. These preferred criteria define other important study design features or attributes and are considered collectively (Table 1). Most criteria described below can be applied to both the studies and risk estimates, though criteria applicable only to risk estimates are noted.

Preferred criteria are developed to ensure study quality and suitability to a benefits analysis and established prior to evaluating any individual study or risk estimates. Conversely, EPA does not consider factors such as the magnitude or variance of the reported risk estimate; accounting for these factors might inadvertently bias our choice of studies or risk estimates.<sup>14</sup>

Each preferred criteria (Table 1) is considered when identifying studies and risk estimates best for use in benefits assessment. Table 2 identifies specific attributes within each preferred criterion that make a particular study more (or less) suitable for a benefits analysis. In practice, no single study or risk estimate will possess the ideal attributes for all criteria and thus we consider the collective merits of any study or risk estimate. This means that the risk estimates ultimately identified for application in benefits assessment may not be the highest ranked in each individual preferred study criterion category, but that they rise to the top when all criteria are considered simultaneously.

Table 1. Criteria for Identifying Studies and Risk Estimates to Use in a Benefits Assessment

<b>Study Attributes<sup>1</sup></b>	<b>Key Factors to Consider when Evaluating Study Quality</b>
Study Period	Studies examining a relatively longer period of time (and therefore having more temporal coverage) are preferred because they have greater statistical power to detect effects (e.g., all else being equal, a study over a five-year duration would be preferred over a study duration of one year). Studies that are more recent are also preferred because of possible changes in pollution mixes, medical care, and lifestyle over time. When identifying risk estimates, models with the broadest time coverage and overlapping air quality and health data are preferred.
Exposure Estimate	Studies estimating air quality/exposure using a combination of approaches (e.g., remote sensing techniques ground-truthed by monitoring data) are preferred over those that use a single method (e.g., monitor data), because multiple measurement methods are less prone to exposure estimate bias and generate higher-resolution of estimates than exposure data

<sup>14</sup> Forest plots of the magnitudes of central risk estimates and associated confidence intervals from epidemiologic studies evaluated by the ISAs by health endpoint can be found in the respective ISAs (U.S. EPA (2019). Integrated Science Assessment (ISA) for Particulate Matter (Final Report). U. S. EPA. Research Triangle Park, NC, U.S. Environmental Protection Agency, Office of Research and Development, Center for Public Health and Environmental Assessment, U.S. EPA (2020). Integrated Science Assessment for Ozone and Related Photochemical Oxidants (Final Report). O. o. R. a. Development. Washington, DC, U.S. Environmental Protection Agency.). These figures illustrate the heterogeneity in the size of the reported effect among this subset of studies and risk estimates.

	from a single source. When available, studies of long-term/chronic exposure are preferred over short-term exposure (i.e., hours up to 1 month), considering the limitations of each exposure duration, as risk estimates based on long-term exposures may include some short-term exposure effects and provide a more comprehensive estimates of health impacts.
Study Type	Among epidemiologic studies that consider long-term exposure (e.g., one month to years), cohort studies are preferred over case-control <sup>15</sup> studies when estimating benefits across the U.S., as they are more representative of the overall population, and both are preferred over cross-sectional <sup>16</sup> or ecological <sup>17</sup> studies because they control for important individual-level confounding. An exception to the preference for cohort studies is for rare disease, when case-control studies may have more power and less selection bias. For short-term exposure studies, case-crossover and time series studies are preferred over cross-sectional or prevalence studies also because they are better able to control for potential confounders.
Population Attributes	Study populations representative (in terms of age, sex, race/ethnicity, etc.) of the population in which health effects are supported are preferred. The most technically appropriate measures of benefits would be based on health impact functions that cover the entire sensitive population but allow for effect modification by age, sex, race/ethnicity, or other relevant demographic factors (e.g., educational status). In the absence of effect estimates specific to age, sex, preexisting condition status, or other relevant factors, it may be appropriate to identify effect estimates that cover the broadest population to match with the desired outcome of the analysis, which for most EPA benefit-cost analyses is total national-level health impacts. Where both are available, both age-stratified and overall risk estimates should be considered for inclusion.
Study Location	Studies conducted in either the U.S. or Canada and representing air quality conditions, affected populations, and other underlying characteristics of the U.S are preferred. <sup>18</sup> U.S. or Canadian studies are preferred because studies conducted elsewhere may exhibit influences of potential differences in pollution characteristics, exposure patterns, medical care system, population behavior, and lifestyle. National estimates are most appropriate when benefits are nationally distributed; the impact of regional differences may be important when benefits only accrue to a single area. City-specific risk estimates from multi-city studies of hospital admissions or emergency department visits for non-fatal morbidities may be evaluated for site-specific application to the corresponding city. Studies using data from non-U.S. locations studies are considered when U.S study options are limited or less informative. Similarity to the U.S. context is a priority for non-U.S. studies. Risk estimates with the broadest geographic coverage are preferred (e.g., multi-city studies preferred to single-city studies) because they provide a more generalizable representation of the health impacts.
Health Endpoint	To comprehensively capture the suite of attributable public health impacts and increase the power to detect effects, when estimating hospital admissions and emergency department visits, broad health endpoints are preferred over narrower, more specific endpoints. For

<sup>15</sup> Retrospective study in which two groups, differing in a health outcome, are identified and compared based on some hypothesized causal characteristic or exposure.

<sup>16</sup> Analysis of a cross-section of a population at a single point in time.

<sup>17</sup> Comparison of groups, rather than individuals.

<sup>18</sup> While there are differences between the U.S. and Canada, notably with regards to the health care systems, there is considerable pollutant transport between Canada and the US, ~90% of Canadians live within ~100 miles of the US border, and ambient PM<sub>2.5</sub> concentrations are similar in Canada and the US (Canada, E. a. C. C. (2016). Canada-United States Transboundary Particulate Matter Science Assessment 2013, Environment and Climate Change Canada, CBC (2016). Canada by the Numbers. [CBC News](#). Online, U.S. EPA (2019). Policy Assessment for the Review of the Ozone National Ambient Air Quality Standards, External Review Draft. U. S. EPA. Research Triangle Park, NC, U.S. Environmental Protection Agency, Office of Air Quality Planning and Standards, Health and Environmental Impacts Division.).

	example, more-inclusive respiratory hospital admissions endpoint would be selected over combining hospital admissions for various individual respiratory endpoints, such as asthma, long-term obstructive pulmonary disease, and respiratory infection. Please note, broad endpoint categories do not overlap (e.g., nervous system effects and respiratory effects), so there is no potential for double counting impacts.
Study Size	Studies examining a relatively large sample are preferred because they generally have more power to detect small magnitude effects. A large sample can be obtained in several ways, including through a large study population, through repeated observations on a smaller population (e.g., through a symptom diary recorded for a panel of asthmatic children) or through a case crossover study design. Study sizes are subject to diminishing returns when the number of subjects become very large (e.g., millions) and thus relatively larger study sizes (i.e., not necessarily the largest study sizes) are preferred.
Pollutant Concentrations	Studies evaluating air pollutant exposures closer to, or below, current conditions are preferred, as the risk associated with exposure may change at different pollutant concentrations and air pollution concentrations may decrease in the future.
Hazard/Risk Estimate	Studies evaluating multiple well-established statistical models adjusted for the most relevant covariates are preferred.
Inclusion of Other Pollutants	When estimating the effects of O <sub>3</sub> and PM (or other pollutant combinations) jointly, it is preferable to use properly specified health impact functions that include both pollutants. Using single-pollutant estimates in cases where both pollutants are expected to affect a health outcome can lead to double-counting of benefits when pollutants are correlated.
Lag Period	Lag durations were identified according to the hierarchy described in Table A-1 of the PM and O <sub>3</sub> ISAs. Briefly, the strongest multi-day/distributed lag periods that are more biologically plausible are preferred.
O <sub>3</sub> Season	Studies and risk estimates of O <sub>3</sub> exposure for the full year are preferred over those estimating O <sub>3</sub> exposures in the summer or warm season only, as O <sub>3</sub> concentrations can remain relatively high outside of the standard warm season in many parts of the country. As such, year-round time coverage can provide a more complete estimate of O <sub>3</sub> exposure health impacts.
O <sub>3</sub> Metric	Risk estimates based on changes in the maximum daily 8-hour average (MDA8) O <sub>3</sub> concentration are preferred. As discussed in the 2020 PM Policy Assessment (PA), there is considerable support from human chamber and epidemiologic studies, as well as advice from EPA's Clean Air Scientific Advisory Committee (CASAC) to support relationships between an 8-hour exposure period and short- and long-term health impacts of O <sub>3</sub> ((U.S. EPA 2020)).

<sup>1</sup> Although preferred criteria categories are not hierarchical, not all criteria are weighted equally, and expert judgement is involved.

### 2.1.2.1 *Prioritizing Preferred Identification Criteria*

Where Table 1 provides general information on how we determine which studies and risk estimates best characterize U.S. risk, Table 2 describes how the attributes for each of the 13 criteria are prioritized within each criteria category. Again, we use the overall study information, and studies ultimately identified generally performed better across all categories. Importantly, the order of prioritization presented in Table 2 are relative. For example, the most preferred option may be considered only slightly more preferable than the other alternative.

Table 2. Rank-ordered priority

Study Attributes	Rank-Ordered Criteria to Consider when Evaluating Study Quality
Study Period	1. Most recent years with overlapping air quality and health data



Study Attributes	Rank-Ordered Criteria to Consider when Evaluating Study Quality		
	2. Less recent years with partially overlapping air quality and health data 3. Studies with air quality monitoring conducted prior to 2000		
Exposure Estimate	1. Studies estimating exposure using a combination of approaches (e.g., chemical transport modeling, monitoring data, land use regression techniques, and satellite data) 2. Studies estimating exposure using some, but not all, of the above approaches (prioritized if using monitoring data and/or chemical transport modeling) 3. Studies estimating exposure using monitoring data only (prefer data from federal reference [FRM] monitors)		
Study Type	<table border="0" style="width: 100%;"> <tr> <td style="width: 50%; vertical-align: top;"> <i>Long-Term Exposure (i.e., one month to years) Studies</i>            1. Cohort studies<sup>2</sup>            2. Case-control studies         </td> <td style="width: 50%; vertical-align: top;"> <i>Short-Term Exposure (i.e., hours up to one month) Studies</i>            1. Case-crossover (each subject serves as own control)/Time series studies<sup>1</sup>            2. Cross-sectional/prevalence (population-level) studies         </td> </tr> </table>	<i>Long-Term Exposure (i.e., one month to years) Studies</i> 1. Cohort studies <sup>2</sup> 2. Case-control studies	<i>Short-Term Exposure (i.e., hours up to one month) Studies</i> 1. Case-crossover (each subject serves as own control)/Time series studies <sup>1</sup> 2. Cross-sectional/prevalence (population-level) studies
<i>Long-Term Exposure (i.e., one month to years) Studies</i> 1. Cohort studies <sup>2</sup> 2. Case-control studies	<i>Short-Term Exposure (i.e., hours up to one month) Studies</i> 1. Case-crossover (each subject serves as own control)/Time series studies <sup>1</sup> 2. Cross-sectional/prevalence (population-level) studies		
Population Attributes	Prefer studies that include broad population attributes with diverse race/ethnicities, both sexes, and broader age groups (e.g., 0-99 as opposed to only ages 0-17 or only ages 65-99)		
Study Location	1. Nationwide coverage (most or all states represented), including rural areas 2. Nationwide coverage, including only urban areas 3. Multi-city and multi-state coverage 4. Multi-city or multi-state coverage 5. Single-city or -state coverage		
Health Endpoints	1. <b>Broad</b> hospital admissions and emergency department visit endpoint categories (e.g., hospital admissions and emergency department visits for cardiovascular and respiratory effects as opposed to admissions or emergency department visits by individual ICD codes) and <b>broad</b> age groups (e.g., 0-99 as opposed to only 0-17 or only 65-99) 2. <b>Broad</b> hospital admissions and emergency department visit health endpoint categories and <b>specific</b> age groups 3. <b>Specific</b> hospital admissions and emergency department visit health endpoint categories and <b>broad</b> age groups 4. <b>Specific</b> hospital admissions and emergency department visit health endpoints and <b>specific</b> age groups Note: The first two options are highly preferred over the second two options		
Study Size	Larger study size preferred		
Pollutant Concentrations	Pollutant exposures concentrations closest to current conditions preferred.		
Hazard/Risk Estimate	1. Risk estimates including the most relevant covariates (e.g., age, sex, race, education, smoking status, etc.) 2. Risk estimates including some relevant covariates 3. Risk estimates that do not include relevant covariates		
Inclusion of Other Pollutants	1. Multipollutant risk estimates including other pollutants and not likely to be affected by collinearity among pollutant covariates. 2. Copollutant risk estimates including either PM <sub>2.5</sub> or O <sub>3</sub> . 3. Single-pollutant risk estimates.		
Lag Period	1. Distributed lag models 2. Average of multiple days (e.g., 0-2) 3. A priori lag days 4. Individual lag days, using expert judgment to identify the appropriate result to focus on considering the time course for physiologic changes for the health effect or outcome being evaluated.		
O <sub>3</sub> Season	Annual/full-year exposures are preferred over summer/warm season-only O <sub>3</sub> exposures for long-term exposure-related health endpoints. Summer/warm season-only exposures are		

Study Attributes	Rank-Ordered Criteria to Consider when Evaluating Study Quality
	preferred over annual/full-year exposures for short-term O <sub>3</sub> exposure-related health endpoints.
O <sub>3</sub> Metric	<ol style="list-style-type: none"> <li>1. 8-hour maximum O<sub>3</sub></li> <li>2. 1-hour maximum O<sub>3</sub></li> <li>3. 24-hour average O<sub>3</sub></li> <li>4. Other metrics</li> </ol>

ICD- International Statistical Classification of Diseases and Related Health Problems

<sup>1</sup>If a study presents both case crossover and time series results, case crossover will be identified

<sup>2</sup>An exception to the preference for cohort studies is for rare disease, when case control studies may have more power and less selection bias.

## 2.2 AVAILABLE EPIDEMIOLOGIC LITERATURE

We follow a structured and transparent process to identify individual epidemiologic studies from the large body of available epidemiologic literature (section 2.1). This process involves the identifying health endpoints that are both attributable to exposure (section 2.2.1) and for which we can quantify counts of cases (section 2.2.2). This literature is then evaluated using the criteria identified in Table 1 and Table 2.

### 2.2.1 Identification of Exposure-Attributable Health Outcomes

Our procedure for identifying exposure-attributable health endpoints is informed by the findings of the Integrated Scientific Assessment (ISA), which identifies broad endpoint categories causally related to pollutant exposure (section 2.2.1.1); these findings are in turn supported by plausible biological pathways of disease (section 2.2.1.2).

Each “candidate” health endpoint must satisfy the below conditions prior to being included in the main benefits assessment:

- The endpoint category (e.g., respiratory effects) is causally related to exposure (section 2.2.1.1)
- The specific health endpoint (e.g., exacerbated asthma) is a biologically plausible health effect of exposure (section 2.2.1.2)

The review of the National Ambient Air Quality Standards (NAAQS) follows a structured and transparent process for evaluating scientific information reported in the ISAs when determining whether a given endpoint is causally related to the pollutant. ISAs transparently identify, critically evaluate, and synthesize the current scientific literature, including epidemiology studies, making them a suitable source of 1) the causal relationships between exposure and health outcomes<sup>19</sup> (section 2.2.1.1), and 2) available epidemiologic literature from which to identify studies and risk estimates for consideration in benefits assessments (section 2.2.3).

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<sup>19</sup> While ISAs form causal determinations for broad endpoint categories (e.g., respiratory effects), which are generally preferred over specific health endpoints (e.g., hay fever symptoms) for comprehensive benefits assessments, they do not make causal determinations for each specific health endpoint. Instead, the ISAs provide information on the strength and consistency of the evidence supporting more specific endpoints within each broad category. The strength and consistency of evidence supporting relationships with specific health endpoints, together with the broad category causality determinations, are used when identifying specific health endpoints for inclusion in benefits assessments.

Our use of the ISAs to select among endpoints is consistent with the advice provided by a 2002 National Academy of Science review, which found that “the goal of health benefits analysis is to consider all relevant health outcomes” and “a comprehensive discussion of causality is not necessary for a benefits analysis” if the information is “provided in the scientific documentation for the rule-making, such as the criteria document and other related reports, and in guidance provided by EPA’s Science Advisory Board” ((NRC 2002)). For background, we provide a “brief review of the evidence for causality” from the most recent ISAs to “provide justification for inclusion and exclusion of specific health outcomes considered” and to acknowledge “uncertaint[ies] associated with this assumption” (section 2.2.1). This section of the TSD also provides background information with regard to potential biological plausibility pathways presented in the ISAs (section 2.2.1.2) that support the causality determinations.

In addition to the causality determinations, ISAs can also serve as a curated source of pollutant-, exposure-, and endpoint-specific available epidemiologic literature. Each ISA begins with a broad, thoroughly documented literature search, the results of which undergo several screening stages to ensure included studies are within the clearly defined scope of each ISA, in order to identify the most policy-relevant science ((U.S. EPA 2015, U.S. EPA 2019)).<sup>20</sup> As such, EPA relies on the systematic and Clean Air Scientific Advisory Committee-reviewed ISAs for criteria pollutant health endpoints and began the process of identifying epidemiologic risk estimates for PM<sub>2.5</sub>- and O<sub>3</sub>-attributable benefits assessment with the literature sets identified in the 2019 PM, 2022 PM Supplement, and 2020 O<sub>3</sub> ISAs ((U.S. EPA 2019, U.S. EPA 2020, U.S. EPA 2022)). All epidemiologic studies newly considered for use in benefits estimation are available in a separate Study Information Table, described in section 2.2.3.

#### *2.2.1.1 ISA Causality Determinations*

ISAs characterize the strength and consistency of underlying human clinical, animal toxicological, and epidemiologic evidence when assessing the causal relationship between each pollutant and health outcome. Generally, to estimate the pollutant-attributable human health benefits in which we are most confident, we estimate benefits resulting from health effects that we have high confidence are attributable to pollutant exposure, so we focus on categories identified as having a “causal” or “likely to be causal” relationship with the pollutant of interest in the most recently published ISA.<sup>21</sup> These causality determinations are applied to broad health endpoint categories (e.g., mortality, cardiovascular

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<sup>20</sup> Studies identified for the 2019 PM ISA were based on the review’s opening “call for information” (79 FR 71764, December 3, 2014), as well as literature searches conducted routinely to identify and evaluate “studies and reports that have undergone scientific peer review and were published or accepted for publication between January 1, 2009 and March 31, 2017. A limited literature update identified some additional studies that were published before December 31, 2017” (U.S. EPA (2009). Integrated Science Assessment for Particulate Matter (Final Report). U. S. EPA. Research Triangle Park, NC, Office of Research and Development, National Center for Environmental Assessment, U.S. EPA (2019). Integrated Science Assessment (ISA) for Particulate Matter (Final Report). U. S. EPA. Research Triangle Park, NC, U.S. Environmental Protection Agency, Office of Research and Development, Center for Public Health and Environmental Assessment., Appendix, p. A-3). For the 2020 O<sub>3</sub> ISA that date was March 30, 2018. Relevant studies published after these dates were provisionally considered by the EPA for the final PM and O<sub>3</sub> NAAQS 2020 decisions but were not found to materially change any of the broad scientific conclusions regarding the health effects of PM and O<sub>3</sub> exposure made in the 2019 PM ISA and 2020 O<sub>3</sub> ISAs. This process ensures a thorough and transparent strategy for literature identification.

<sup>21</sup> This is not to imply that there may not be benefits associated with endpoints having a “suggestive of, but not sufficient to infer, a causal relationship” but rather that there is greater uncertainty associated with estimating these potential benefits (section 1.2). While these benefits are not included in the main assessment, they may be included in sensitivity analyses.

effects, respiratory effects, nervous system effects, metabolic effects, etc.) using a weight-of evidence approach ((U.S. EPA 2015, U.S. EPA 2019)), according to the rationale described below:<sup>22</sup>

- *Causal relationship*- Evidence is sufficient to conclude that there is a causal relationship with relevant pollutant exposures (e.g., doses or exposures generally within one to two orders of magnitude of recent concentrations). That is, the pollutant has been shown to result in health effects in studies in which chance, confounding, and other biases could be ruled out with reasonable confidence. For example: (1) controlled human exposure studies that demonstrate consistent effects, or (2) observational studies that cannot be explained by plausible alternatives or that are supported by other lines of evidence (e.g., animal studies or mode-of-action information). Generally, the determination is based on multiple high-quality studies conducted by multiple research groups.
- *Likely to be causal relationship*- Evidence is sufficient to conclude that a causal relationship is likely to exist with relevant pollutant exposures. That is, the pollutant has been shown to result in health effects in studies where results are not explained by chance, confounding, and other biases, but uncertainties remain in the evidence overall. For example: (1) observational studies show an association, but copollutant exposures are difficult to address and/or other lines of evidence (controlled human exposure, animal, or mode of action information) are limited or inconsistent or (2) animal toxicological evidence from multiple studies from different laboratories demonstrate effects but limited or no human data are available. Generally, the determination is based on multiple high-quality studies.

Conclusions made in the 2019 PM, 2022 supplemental PM and 2020 O<sub>3</sub> ISAs regarding the relationships between exposure and various broad health endpoints, as well as previous determinations from the 2009 PM and 2013 O<sub>3</sub> ISAs, are provided below, with “causal” and “likely to be causal” judgements highlighted (Table 3 and Table 4) ((U.S. EPA 2009, U.S. EPA 2013, U.S. EPA 2019, U.S. EPA 2020), (U.S. EPA 2022)).<sup>23</sup> There were no “causal” or “likely to be causal” relationships for PM<sub>10-2.5</sub> or ultrafine particles in the 2019 PM ISA or 2022 supplemental PM ISA, so Table 3 focuses on PM<sub>2.5</sub> determinations.<sup>24</sup> Table 3 also highlights how the causal determinations in the 2019 PM ISA are similar to, or different from, the determinations from the 2009 PM ISA. Table 4 highlights how the new causal determinations in the 2020 O<sub>3</sub> ISA are similar to, or different from, the determinations from the 2013 O<sub>3</sub> ISA. Sections of the 2019 PM and 2020 O<sub>3</sub> ISAs related to “causal” and “likely to be causal” determinations were used as the basis for identifying the set of available epidemiologic literature best suited for consideration in benefit estimation ((U.S. EPA 2009, U.S. EPA 2013, U.S. EPA 2019, U.S. EPA 2020)), as discussed in more detail on section 2.3.

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<sup>22</sup> See Preamble to Integrated Science Assessments, EPA/600/R-15/067, <https://cfpub.epa.gov/ncea/isa/recordisplay.cfm?deid=347534>

<sup>23</sup> Full summaries of causality determinations by exposure duration and health outcome are available in Table ES- of both the 2019 PM and 2020 O<sub>3</sub> ISAs. The 2022 Supplemental PM ISA did not update causality determinations, but instead updated the literature associated with cardiovascular and mortality outcomes (U.S. EPA (2022). Supplement to the 2019 Integrated Science Assessment for Particulate Matter (Final Report). U. S. EPA. Research Triangle Park, NC, U.S. Environmental Protection Agency, Office of Research and Development, Center for Public Health and Environmental Assessment.).

<sup>24</sup> Ultrafine particles are generally considered to have an aerodynamic diameter less than or equal to 0.1 μm.

Table 3. Causality Determined for PM<sub>2.5</sub>-Related Health Effects

Exposure	Health Outcome	2009 ISA Determinations	2019 ISA Determinations <sup>23</sup>
<i>Long-term</i>	Mortality <sup>1</sup>	Causal	Causal
	Cardiovascular Effects	Causal	Causal
	Respiratory Effects	Likely to be causal	Likely to be causal
	Nervous System Effects	None	Likely to be causal
	Cancer	Suggestive of, but not sufficient to infer	Likely to be causal
	Metabolic Effects	None	Suggestive of, but not sufficient to infer
	Male and Female Reproduction and Fertility	Suggestive of, but not sufficient to infer	Suggestive of, but not sufficient to infer
	Pregnancy and Birth Outcomes	Suggestive of, but not sufficient to infer	Suggestive of, but not sufficient to infer
<i>Short-term</i>	Mortality <sup>1</sup>	Causal	Causal
	Cardiovascular Effects	Causal	Causal
	Respiratory Effects	Likely to be causal	Likely to be causal
	Metabolic Effects	None	Suggestive of, but not sufficient to infer
	Nervous System Effects	Inadequate to infer	Suggestive of, but not sufficient to infer

<sup>1</sup>Total mortality includes all nonaccidental causes of mortality and is informed by findings for the spectrum of morbidity effects (e.g., respiratory, cardiovascular) that can lead to mortality. Many studies contributing to the total mortality determination assess all causes of mortality. The proportion of cause-specific deaths differs by analysis.

Table 4. Causality Determined for O<sub>3</sub>-Related Health Effects

Exposure	Health Outcome	2013 ISA Conclusion	2020 ISA Conclusion	
<i>Long-term</i>	Respiratory Effects	Likely to be causal	Likely to be causal	
	Cardiovascular Effects	Suggestive of a causal relationship	Suggestive of, but not sufficient to infer, a causal relationship	
	Metabolic Effects	None	Suggestive of, but not sufficient to infer, a causal relationship	
	Total Mortality <sup>1</sup>	Suggestive of a causal relationship	Suggestive of, but not sufficient to infer, a causal relationship	
	Reproductive Effects	Suggestive of a causal relationship	Suggestive of a causal relationship	Effects on fertility and reproduction: suggestive of, but not sufficient to infer, a causal relationship
				Effects on pregnancy and birth outcomes: suggestive of, but not sufficient to infer, a causal relationship
	Central Nervous System Effects	Suggestive of a causal relationship	Suggestive of, but not sufficient to infer, a causal relationship	
<i>Short-term</i>	Respiratory Effects	Causal	Causal	
	Total Mortality <sup>1</sup>	Likely to be causal	Suggestive of, but not sufficient to infer, a causal relationship	

	Cardiovascular Effects	Likely to be causal	Suggestive of, but not sufficient to infer, a causal relationship
	Metabolic Effects	None	Likely to be causal
	Central Nervous System Effects	Suggestive of a causal relationship	Suggestive of, but not sufficient to infer, a causal relationship

<sup>1</sup>Total mortality includes all nonaccidental causes of mortality and is informed by findings for the spectrum of morbidity effects (e.g., respiratory, cardiovascular) that can lead to mortality. Many studies contributing to the total mortality determination assess all causes of mortality. The proportion of cause-specific deaths differs by analysis.

**2.2.1.2 Biological Plausibility**

ISAs draw conclusions regarding the causal nature of relationships between PM and health and non-ecological welfare effects. These conclusions apply to broad health effect categories (e.g., cardiovascular effects) and provide information on the strength and consistency of the evidence supporting more specific endpoints (e.g., heart failure) within each section. Both types of information are utilized in benefits assessments. Broad causality determinations can support the use of more comprehensive endpoints found in epidemiologic studies of hospital admissions and emergency department visits, whereas the support of specific endpoints resulting from pollutant exposure may be more relevant to incidence endpoints such as cardiac arrest.

In forming the key science judgments for each of the health effects categories evaluated, the recent ISAs draw conclusions about relationships between PM and O<sub>3</sub> exposure and health effects by integrating information across scientific disciplines and related health outcomes and synthesizing evidence from previous and recent studies. An advancement in these most recent ISAs is the inclusion of biological plausibility sections that are specific for each exposure duration and broad health outcome category for which causality determinations are formed. These discussions outline potential pathways along the exposure-to-outcome continuum and provide plausible links between pollutant inhalation and health outcomes at the population level. We include unedited diagrams from the biological plausibility sections of the 2019 PM and 2020 O<sub>3</sub> ISAs here to provide information regarding the plausibility of individual health endpoints resulting from PM and/or O<sub>3</sub> exposures.

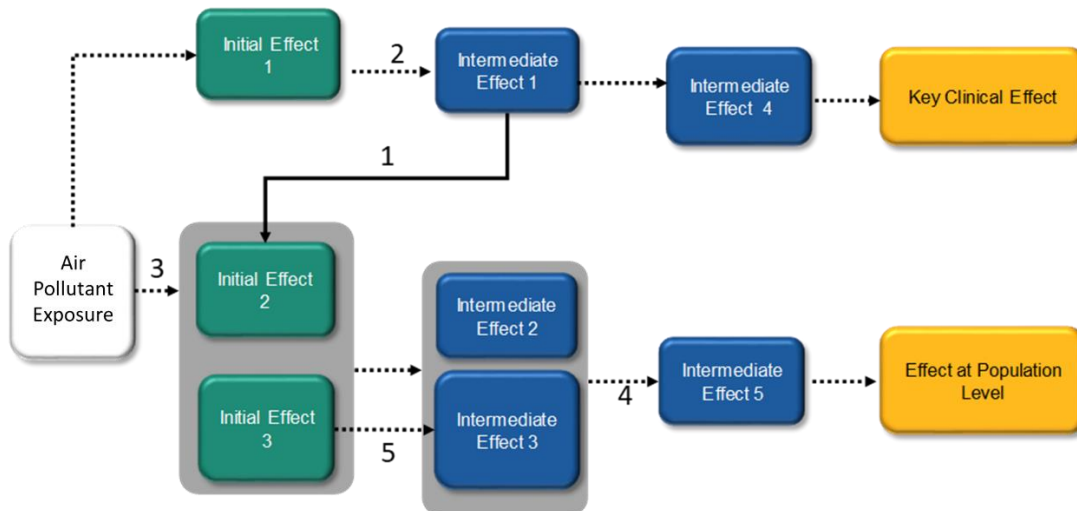
Biological plausibility can strengthen the basis for causal inference ((U.S. EPA 2015)). In the recent ISAs, biological plausibility is part of the weight-of-evidence analysis that considers the totality of the health effects evidence, including consistency and coherence of effects described in experimental and observational studies. Although there is some overlap in the potential pathways between the ISA health effects chapters, each biological plausibility section is tailored to the health outcome category, pollutant, and exposure duration being evaluated within the respective section of each ISA health effects chapter. Diagrams illustrate possible pathways relating exposure to evidence evaluated in current and previous assessments, considering physiology and pathophysiology (Figure 1).<sup>25</sup> These diagrams portray the available evidence that supports the biological plausibility of exposures leading to specific health outcomes, but does not provide information on the weight of evidence supporting each biological pathway (section 2.2.1.2). Gaps and limitations in the evidence base, shown by the absence of a connecting arrow, correspond to gaps in the figure.

<sup>25</sup> Information in the biological plausibility diagrams includes studies identified in previous ISAs and Air Quality Criteria Documents (AQCDs).

Each box represents evidence that has been demonstrated in a study or group of studies for a particular effect related to exposure. While most of the studies used to develop the figures are experimental studies (i.e., animal toxicological and controlled human exposure studies), some observational epidemiologic studies also contribute to the pathways. These epidemiologic studies are generally: 1) panel studies that measure the same or similar effects as the experimental studies (and thus provide supportive evidence) or 2) emergency department and hospital admission studies or studies of mortality, which are effects observed at the population level. The boxes are arranged horizontally, with boxes on the left side representing initial effects that reflect early biological responses and boxes to the right representing potential intermediate (i.e., subclinical or clinical) effects and potential effects at the population level. The boxes are color coded according to their position in the exposure-to-outcome continuum.

The arrows that connect the boxes indicate a potential progression of effects resulting from exposure. In most cases, arrows are dotted (Figure 1, Arrow 1), denoting a possible relationship between the effects. While most arrows point from left to right, some arrows point from right to left, reflecting progression of effects in the opposite direction or a feedback loop (Figure 1, Arrow 2). In a few cases, the arrows are solid (Figure 1, Arrow 2), indicating that progression from the upstream to downstream effect occurs as a direct result of exposure. This relationship between the boxes, where the upstream effect is necessary for progression to the downstream effect, is termed “essentiality” ((OECD 2016)). Evidence supporting essentiality is generally provided by experimental studies using pharmacologic agents (i.e., inhibitors) or animal models in which the molecular pathway is obstructed. The use of solid lines, as opposed to dotted lines, reflects the availability of specific experimental evidence that exposure results in an upstream effect which is necessary for progression to a downstream effect, for example, by a genetically deficient model or a chemical inhibitor used in an experimental study involving pollutant exposure.

In the diagrams, upstream effects are sometimes linked to multiple potential downstream effects. Boxes represent the effects for which there is experimental or epidemiologic evidence related to air pollutant exposure, and the arrows indicate a proposed relationship between those effects. To illustrate the proposed relationship using a minimum number of arrows, downstream boxes are grouped together within a larger shaded box and a single arrow (Figure 1, Arrow 3) connects the upstream single box to the outside of the downstream shaded box containing multiple green boxes. Multiple upstream effects may similarly be linked to a single downstream effect using an arrow (Figure 1, Arrow 4) that connects the outside of a shaded box which contains multiple boxes, to an individual box. In addition, arrows sometimes connect one individual box to another individual box that is contained within a larger shaded box (Figure 1, Arrow 2) or two individual boxes both contained within larger shaded boxes (Figure 1, Arrow 5). Thus, arrows may connect individual boxes, groupings of boxes, and individual boxes within groupings of boxes depending on the proposed relationships between effects represented by the boxes. Population level effects generally reflect results of epidemiologic studies. When there are gaps in the evidence base, there are complementary gaps in the figure and the accompanying text below.



Note: For additional information, please refer to the original biological plausibility diagrams in the ISAs ((U.S. EPA 2019, U.S. EPA 2020)).

Figure 1. Illustrative Diagram of Potential Biological Pathways of Health Effects Following Pollutant Exposure.

#### 2.2.1.2.1 PM<sub>2.5</sub>-Attributable Endpoints and Biological Plausibility

Below are the ISA biological plausibility diagrams for PM<sub>2.5</sub> and O<sub>3</sub> endpoints judged to have either a “causal” and “likely to be causal” relationship with pollutant exposure in the 2019 PM and 2020 O<sub>3</sub> ISAs, as well as information on which of the endpoints identified in the diagrams have or have not been previously included in benefits assessments. These diagrams have been reproduced verbatim from the ISAs, for the convenience of the reader, and no new independent judgements are rendered regarding biological plausibility in this TSD. Although it is not possible to develop a biological plausibility diagram for total mortality, taken together, the individual endpoint-specific biological plausibility diagrams each provide potential pathways by which PM<sub>2.5</sub> exposures could result in mortality.



2.2.1.2.1.1 Cardiovascular Effects

The 2019 PM ISA diagram of biological pathways for cardiovascular effects following short-term PM<sub>2.5</sub> exposure includes emergency department visits and hospital admissions as population level effects, for which EPA has historically presented benefits impact estimates (Figure 2). The diagram also includes mortality as a key endpoint, which EPA has not included in benefits estimates due to the possibility of overlap with all-cause mortality impacts from long-term exposure resulting in double counting.

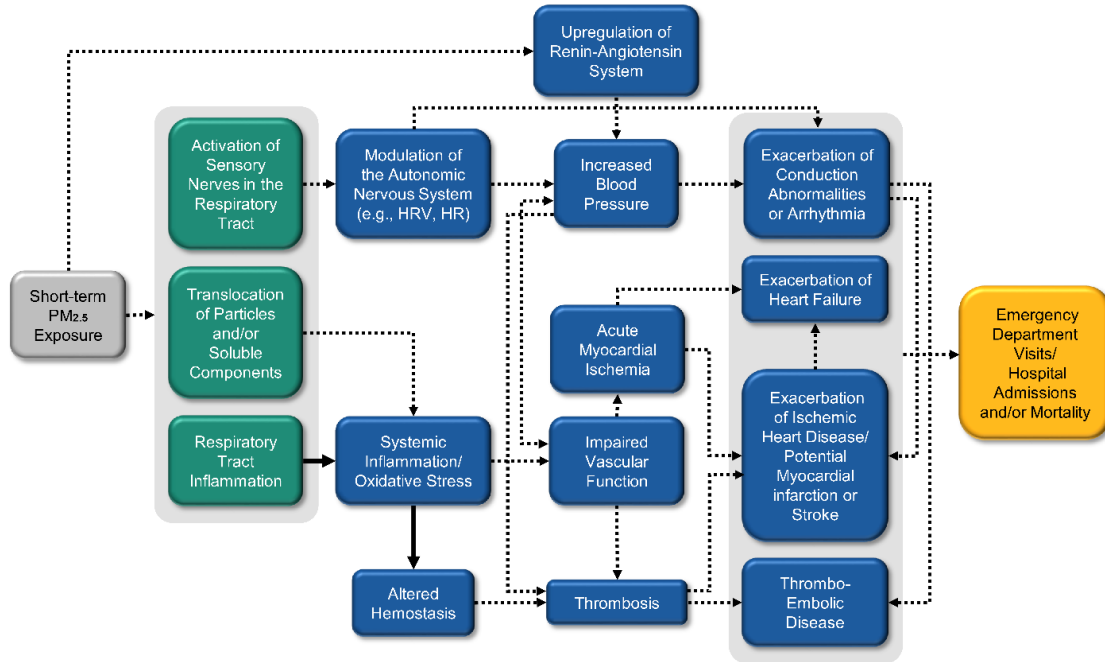


Figure 2. Potential Biological Pathways for Cardiovascular Effects Following Short-Term PM<sub>2.5</sub> Exposure

The 2019 PM ISA diagram of biological pathways for cardiovascular effects following long-term PM<sub>2.5</sub> exposure includes acute myocardial infarctions (AMI; heart attacks) and mortality, which EPA has historically presented benefits impact estimates for, and conductance abnormalities/arrhythmia, heart failure, stroke, and thromboembolic disease, which have not been included in previous benefits estimates (Figure 3).

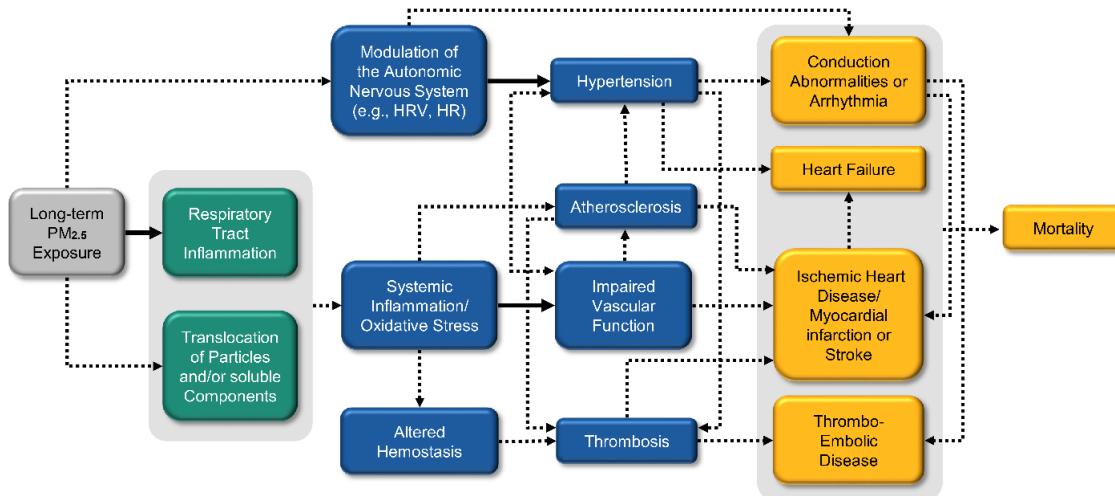


Figure 3. Potential Biological Pathways for Cardiovascular Effects Following Long-Term PM<sub>2.5</sub> Exposure

2.2.1.2.1.2 *Respiratory Effects*

The 2019 PM ISA diagram of biological pathways for respiratory effects following short-term PM<sub>2.5</sub> exposure includes emergency department visits and hospital admissions for asthma exacerbation/symptoms, chronic obstructive pulmonary disease (COPD), and respiratory infections as key population level health endpoints, for which EPA has historically presented benefits impact estimates (Figure 4).

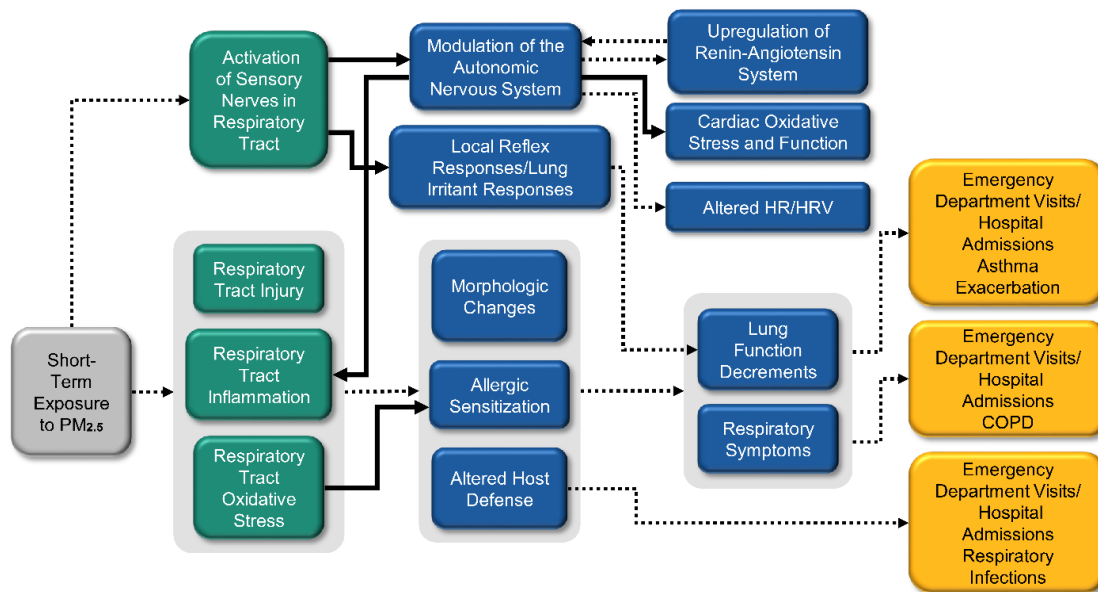


Figure 4. Potential Biological Pathways for Respiratory Effects Following Short-Term PM<sub>2.5</sub> Exposure

The 2019 PM ISA diagram of biological pathways for respiratory effects following long-term PM<sub>2.5</sub> exposure includes asthma development/onset and impaired lung function, for which we have not previously presented benefits impact estimates (Figure 5).

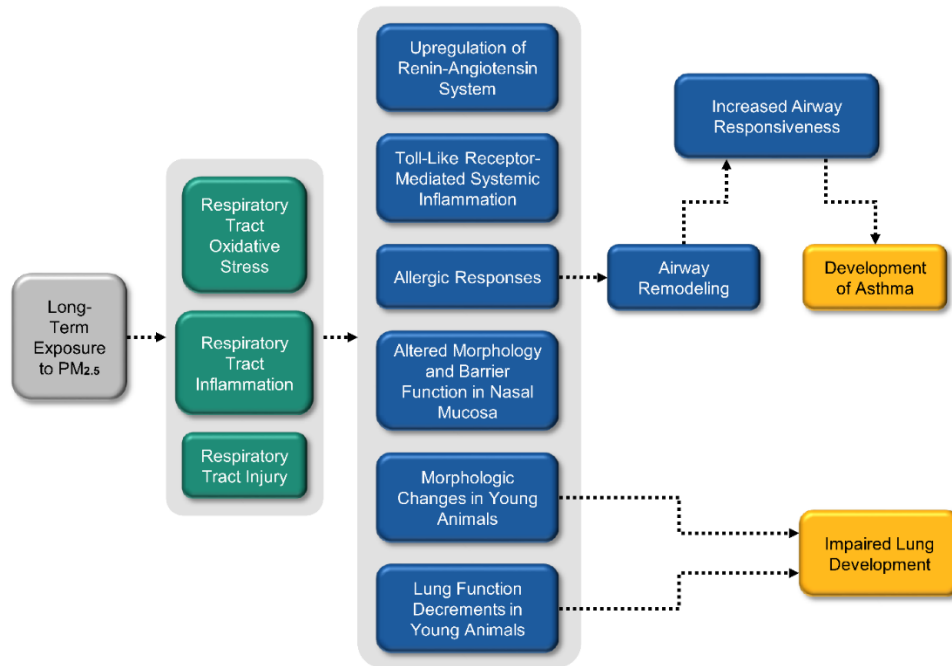


Figure 5. Potential Biological Pathways for Respiratory Effects Following Long-Term PM<sub>2.5</sub> Exposure

2.2.1.2.1.3 *Cancer*

The diagram of biological pathways of cancer following long-term PM<sub>2.5</sub> exposure is provided (Figure 6)., This relationship was “suggestive” in the 2009 PM ISA and “likely to be causal” in the 2019 ISA ((U.S. EPA 2009, U.S. EPA 2019)).

As cancer is a long-term disease, the 2019 PM ISA did not provide a diagram of biological pathways for cancer following short-term PM<sub>2.5</sub> exposure.

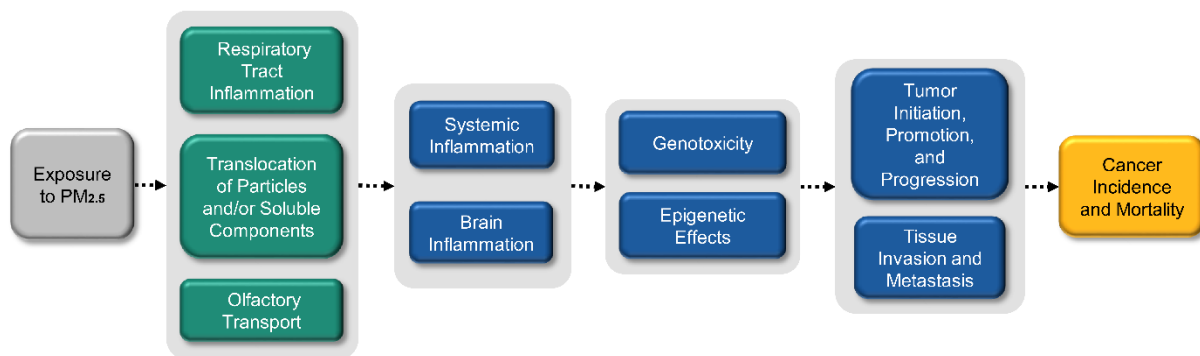


Figure 6. Potential Biological Pathways for Cancer Effects Following Long-Term PM<sub>2.5</sub> Exposure

2.2.1.2.1.4 *Nervous System Effects*

The 2019 PM ISA diagram of biological pathways for nervous system effects following long-term PM<sub>2.5</sub> exposure includes neurodevelopmental disorders, Parkinson’s and Alzheimer’s disease hospital admissions and emergency department visits, cognitive decrements/behavioral effects, and cognitive

issues (Figure 7). Please note, the weight of evidence supporting each potential is not equivalent and additional information can be found in the 2019 PM ISA ((U.S. EPA 2019)). As the previous nervous system effect ISA determination did not rise to the “causal” or “likely to be causal” level, EPA has not previously included any nervous system endpoints in benefits impact estimates.

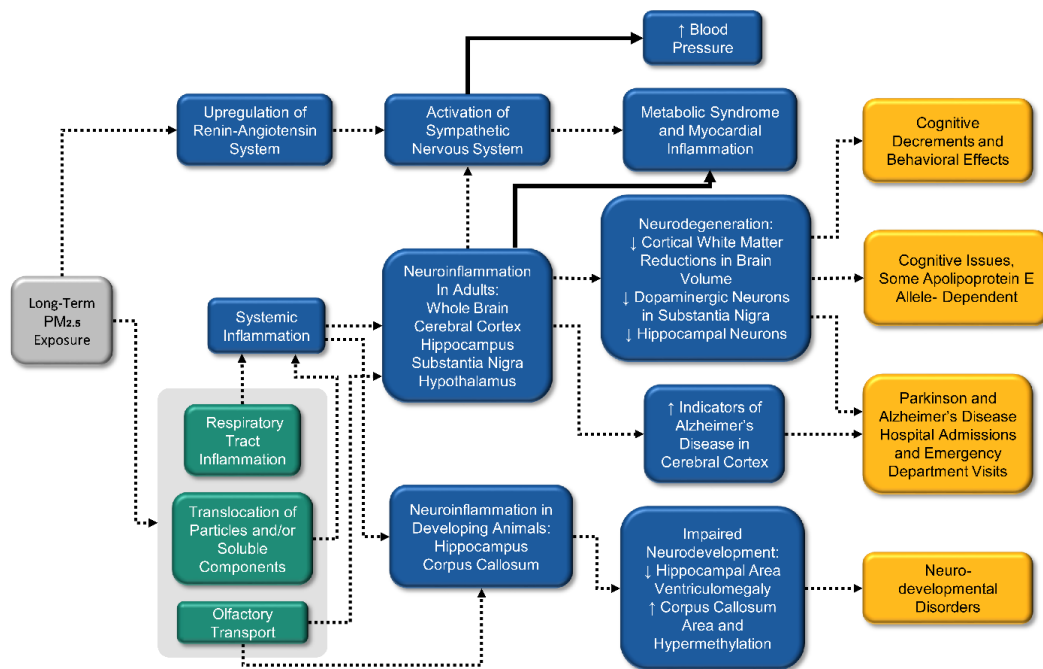


Figure 7. Potential Biological Pathways for Nervous System Effects Following Long-Term PM<sub>2.5</sub> Exposure

#### 2.2.1.2.2 O<sub>3</sub>-Attributable Endpoints and Biological Plausibility

##### 2.2.1.2.2.1 Respiratory Effects

The 2020 O<sub>3</sub> ISA diagram of biological pathways for respiratory effects following short-term O<sub>3</sub> exposure includes emergency department visits and hospital admissions for asthma exacerbation/symptoms and respiratory infections, for which we have historically presented benefits impact estimates, and lung function decrements, which EPA has not previously estimated associated benefits (Figure 8). Although respiratory mortality is supported as a key clinical effect of short-term ozone exposure in the ISA text and should be included in this diagram, it was mistakenly left out due to the expedited timeline of the 2020 O<sub>3</sub> ISA.<sup>26</sup>

<sup>26</sup> This information was obtained through conversations with the authors of the 2020 O<sub>3</sub> ISA.

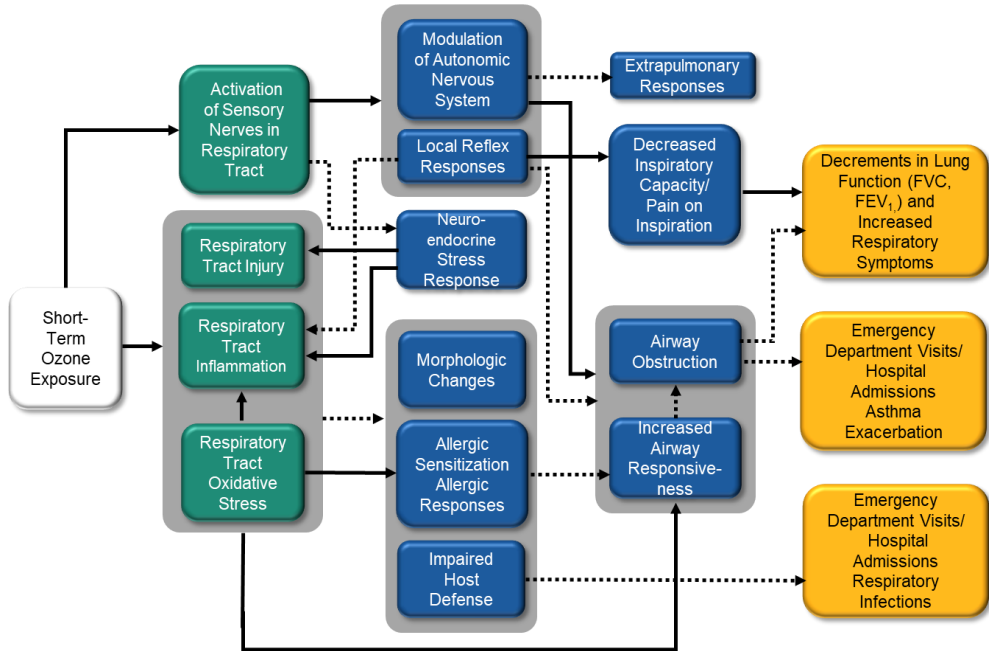


Figure 8. Potential Biological Pathways for Respiratory Effects Following Short-Term O<sub>3</sub> Exposure

The 2020 O<sub>3</sub> ISA diagram of biological pathways for respiratory effects following long-term O<sub>3</sub> exposure includes mortality, which EPA has included in prior benefits assessments, and asthma development/onset, fibrotic- or emphysema-like disease/COPD, and altered lung development, which EPA has not previously included in benefits impact estimates (Figure 9).

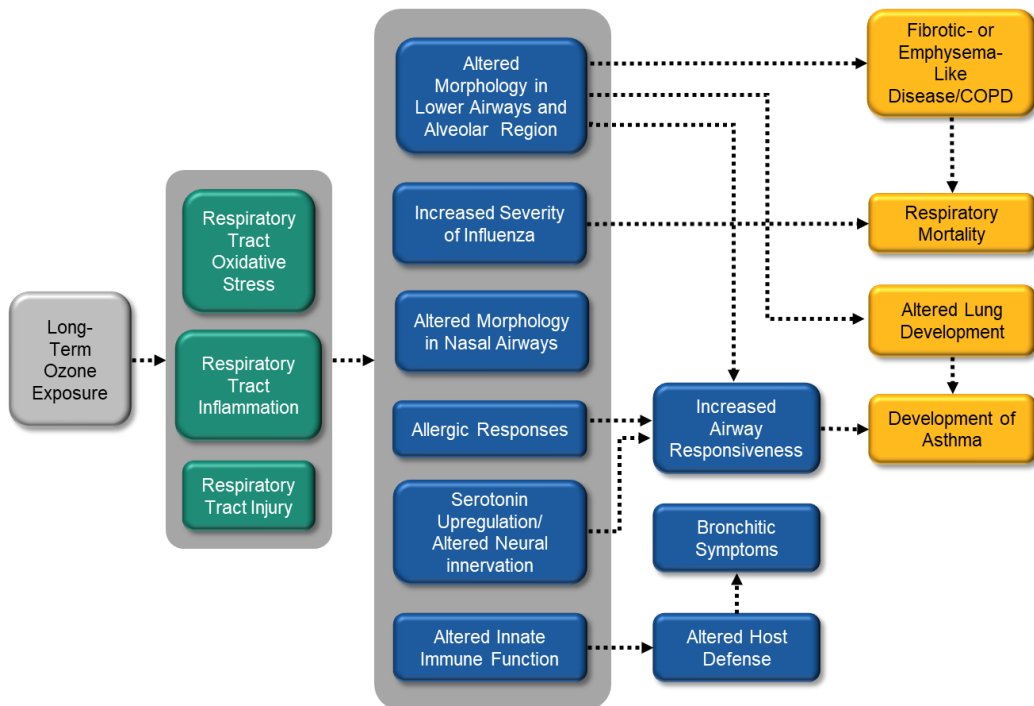


Figure 9. Potential Biological Pathways for Respiratory Effects Following Long-Term O<sub>3</sub> Exposure

2.2.1.2.2.2 *Metabolic Effects*

The 2020 O<sub>3</sub> ISA concluded that short-term exposure was likely to cause metabolic effects and long-term exposure was suggestive of a causal relationship. Neither short- nor long-term causal determinations were made for metabolic effects in the 2013 O<sub>3</sub> ISA. The ISA diagram of biological pathways for metabolic effects indicates that long-term O<sub>3</sub> exposure leads to complications related to diabetes and changes or contributors to metabolic syndrome, which EPA has not previously included in benefits assessments.

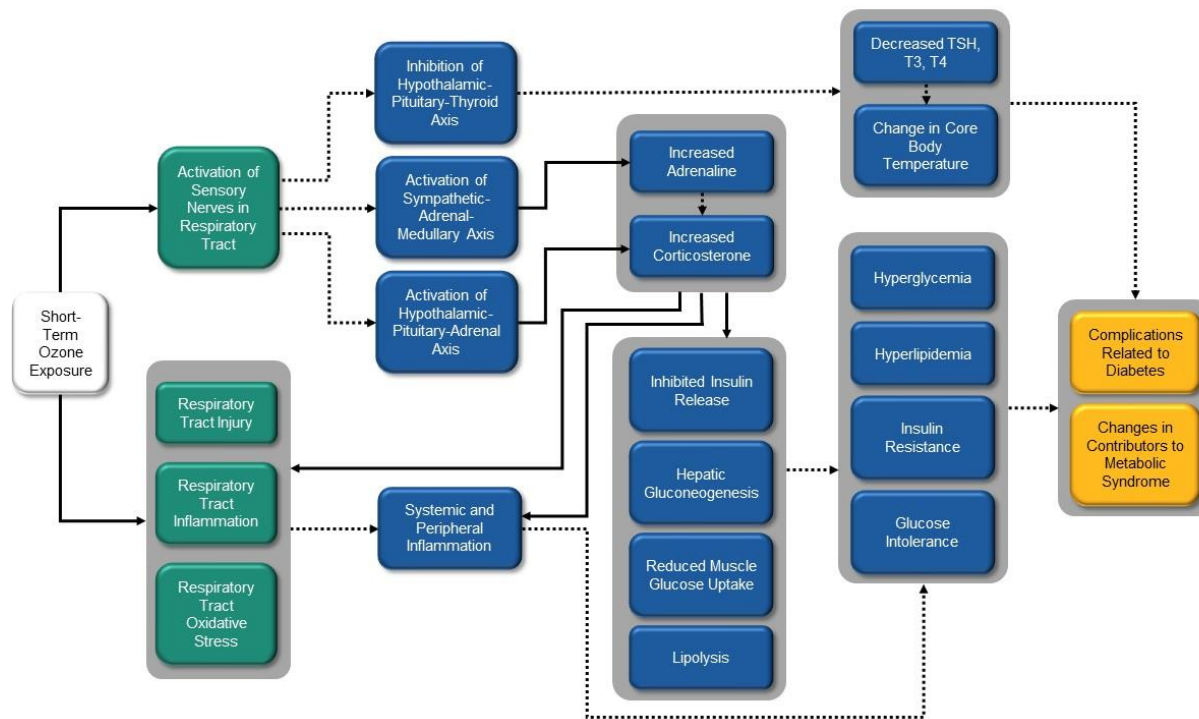


Figure 10. Potential Biological Pathways for Metabolic Effects Following Short-Term O<sub>3</sub> Exposure

2.2.2 Identifying Quantifiable Health Outcomes<sup>27</sup>

Health endpoints referenced in the latest externally reviewed ISA or equivalent assessment include both subclinical and clinically relevant endpoints. However, health impacts assessments tend to focus on quantifying the number of instances of clinically relevant endpoints (e.g., mortality, hospital admissions, and disease onset/development) and not subclinical endpoints (e.g., inflammation, oxidative stress, changes in circulation biomarkers, or changes in heart or lung function) for several reasons.

1. Specific baseline event incidence, or the amount of a particular health endpoint present within the population, is required when using epidemiologic risk estimates to project health impacts of changes in air quality. Baseline incidence data is more likely to be available for clinically relevant

<sup>27</sup> This approach is consistent with the “effect by effect” approach described in the benefits chapter of the *Guidelines for Preparing Economic Analyses* (U.S. EPA (2014). *Guidelines for Preparing Economic Analyses*, National Center for Environmental Economics. US Environmental Protection Agency Washington, DC.). Quantification is treated as separable from monetization given resource and data limitations (section 1.2).

health endpoints (e.g., hospital admissions for cardiovascular ICD codes 390-459 or the prevalence of asthma in children) then for subclinical endpoints (e.g., forced expiratory volume or hypertension).

2. Quantifying subclinical endpoints involve additional uncertainties when relating upstream subclinical effects with clinically relevant downstream health impacts. This does not mean that subclinical health impacts of PM<sub>2.5</sub> and O<sub>3</sub> do not exist. In fact, considerably more instances of pollutant-attributable subclinical effects than clinically relevant effects would be expected.

Although causal determinations are made for broad health endpoint categories (e.g., cardiovascular effects), the ISAs do review support for specific endpoints (e.g., acute myocardial infarctions) (section 2.2.1.2). Evidence associating specific health endpoints falling under broad health endpoints with “likely to be causal” or “causal” relationships with air pollution exposures are used to identify comprehensive, but not overlapping, health endpoints, when suitable studies for quantification based on the criteria identified above are available.

### 2.2.3 Study Information Table

Extensive and comprehensive study information is provided for transparency regarding study comparisons and identification for benefits assessment. Specific study information, corresponding to the preferred criteria in section 2.1.2, is available for all endpoint-specific, ISA-derived epidemiologic studies newly considered for use in the main and sensitivity benefits estimation in a separate Excel file titled *Study Information Table for the Estimating PM<sub>2.5</sub>- and Ozone-Attributable Health Benefits TSD*.<sup>28,29</sup> Specific studies are listed once per pollutant health endpoint.

Descriptions of the specific types of information extracted from the studies and included in the Study Information Table are available in Table 5. Studies differed in the type and level of detail of information provided. Additionally, sometimes information was not reported (NR) by the study and is therefore not available in the Study Information Table. For example, not all studies provided information on the race, sex, age range of the study population. Please note, individual studies may be listed multiple times in the Study Information Table if they report results for multiple endpoints, but they are listed only once per pollutant endpoint.

Table 5. Study Information Tables

Column Name	Description
Endpoint Group	“Causal” or “likely to be causal” health endpoint included in benefits assessment.
Endpoint	Specific health endpoint included in benefits assessment.
HERO ID	Identifier used by the Health and Environmental Research Online (HERO) database. This database is a repository for studies and other references and is used for various peer-reviewed documents, such as ISAs and research projects.
First Author	First study author listed.
Title	Title of the study.

<sup>28</sup> Study information is kept in a separate Excel file to support ease of use.

<sup>29</sup> Risk estimate information tables are not provided as the identification of suitable risk estimates followed the hierarchy described in Table A-1 of the 2019 PM ISA appendix.

Abstract	Abstract of the study.
Publication Year	Year the article was published, according to PubMed.
Pollutant	PM <sub>2.5</sub> or O <sub>3</sub> .
ISA Source	Integrated Science Assessment where study was initially referenced, beginning with the 2019 PM ISA and 2020 Ozone ISA.
Study Type	Epidemiologic study design (e.g., cohort, case control, case crossover, etc.).
Meta-Analysis	Identifies meta-analyses for use when considering pooling city- or regional-specific estimates to generate an overall risk estimate.
Exposure Duration	Long-term (one month to years) or short-term (hours to less than one month) exposures.
Study Population	Cohort name or description if unnamed.
Study Size (number of participants or events)	This can take various forms, such as the number of participants, person-years, number of hospitalizations/admissions/discharges, or number of cases and controls. All information provided by the study is included.
Demographics	Demographics of the study participants, such as race/ethnicity, education level, income level, and socioeconomic status.
Ages	Ages of study participants, with maximum age of 99 reported when maximum participant aged 99 and older.
Exposure Method	Summary of the type of exposure estimate technique. Monitor studies denote monitor-based studies, and often include land use regression (LUR) techniques. Hybrid studies include photochemical model and/or satellite data.
Country	Location of study population (U.S. or Canada).
Study Location	Brief description of the locations included in the study.
Health Years	Years of health data included.
Air Quality Years	Years of air quality data included. Many studies used a specific common time frame for entire sample, but some used other criteria, such as exposure over the first year of life.
Pollutant Concentrations (author-reported)	Typically, the overall mean and/or median concentrations across study areas, but sometimes provided information was at a different geographic and temporal scales (e.g., by state and over multiple years).
LRL/Minimum Exposure Concentration	The lowest reported pollutant level/concentration.
Pollutant Concentration Notes	Author-reported exposure estimation method. If multiple types of exposure estimation techniques were used for an individual pollutant, all are included.
Outcome Measure	Specific health outcome. Examples include the ICD codes used for hospital admission and emergency department visits or the criteria used to identify disease onset.
Lag Periods	For short-term studies, the time period of exposure prior to health effect.
Copollutants	Adjustments for copollutants in the risk estimates.
Covariates/Confounders	Author-reported covariates/confounders included in the risk estimate.
Statistical Technique	Analytical methods used to generate the risk estimate.
Qualitative Limitations	Summary comparison of each study to others investigating the same pollutant and specific health endpoint.
Relative Determination	Denotes which studies were identified as best characterizing risk as compared to other available studies for each pollutant endpoint.



## 2.2.4 Methods for Presenting Health Benefits Estimates Using Multiple Risk Estimates for a Single Endpoint

### 2.2.4.1 Pooling

If more than one study or risk estimate is suitable for characterizing risk across the U.S. for an individual health endpoint, we prefer to use multiple risk coefficients to the extent technically feasible. In such instances, we combine the risk estimates using pooling<sup>30</sup> methods in order to avoid a loss of information from multiple suitable studies; this approach is consistent with advice received from the National Academies of Sciences ((NRC 2002)). Pooling yields a summary mean value estimate and confidence intervals reflecting variability across the pooled risk estimates. These pooled estimates account for both the within-study variances and the between-study variance when weighting.

Multiple epidemiology studies might assess a common endpoint using very different input parameters and analytical assumptions,<sup>31</sup> making it difficult to pool this literature. For example, it would be inadvisable to combine results from a long-term exposure study with a short-term exposure study. Other types of study heterogeneity that would prevent one from aggregating across studies include exposure duration (i.e., short- and long-term), some population attributes (e.g., age or race/ethnicity), health endpoint outcome measure (e.g., specific international classification of disease [ICD] codes), and study type (e.g., cohort vs case control).

Recently developed hybrid methods for estimating population exposure allow researchers to characterize pollutant concentrations at more detailed temporal and spatial scales than those methods using monitoring data alone. As the uncertainties associated with hybrid- and monitor-based exposure estimates vary and we consider the quality of the exposure estimate during study and risk estimate identification, we expect pooling risk estimates that vary by exposure technique will increase the confidence in the overall benefits estimate.

Conversely, while consistency between studies is generally desirable when pooling, there are some instances when it could introduce uncertainty and/or bias. For example, pooling Hazard Ratios reported in two or more studies of the same cohort, or Hazard Ratios reported for alternative cohorts, poses special challenges; this procedure generally requires individual-level data not readily available for most cohorts ((Burnett, Chen et al. 2018)). Hence, we would instead identify the most recent analysis or the analysis considering the longest time series of air quality data, so that the study population is not over-represented when estimating health impacts.<sup>32</sup>

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<sup>30</sup> Pooling estimates would be accomplished by performing a meta-analysis, a statistical method of aggregating independent risk estimates by weighting each study according to the inverse of the reported variance, generating a single estimate. EPA has in the past sought to characterize the magnitude of uncertainty across risk estimates by either applying a fixed effect or random effects pooling technique to combine two or more risk estimates.

<sup>31</sup> This is considered a strength when determining whether an outcome is causally linked to a pollutant.

<sup>32</sup> If multiple studies of the same cohort suitably characterize risk, multi-step pooling to avoid over-weighting is an option. This would involve first combining analyses of the same cohort and then combining with estimates from other cohorts.

#### 2.2.4.2 Individual Alternate Risk Estimates

In situations where multiple risk estimates should not or cannot be pooled<sup>33</sup>, we instead estimate incidence using each individual risk estimate. Where pooling synthesizes the results of multiple risk estimates into a single value, presenting multiple estimates from various key epidemiological studies identified by the latest ISA or equivalent could provide readers with insight to the plausible range of air pollution-attributable impacts. Therefore, if pooling is infeasible due to the issues mentioned above, we report individual results from each risk estimate suitable for characterizing risk across the U.S. for an individual health endpoint separately. Reporting many individual estimates may characterize the heterogeneity associated with risk but may also make the resulting risk estimates more difficult to interpret. To keep results manageable, we may report additional estimates as a quantitative sensitivity analysis.

### 2.3 SYSTEMATICALLY IDENTIFYING EPIDEMIOLOGIC STUDIES AND RISK ESTIMATES FOR BENEFITS ASSESSMENT

This section describes the systematic application of the identification criteria (section 2.1) to the body of available epidemiologic studies and risk estimates (section 2.2). Summary information on the number of available and included studies and risk estimates is presented in Table 6 and Table 7. Descriptions of endpoint-specific ISA support and available epidemiologic literature are available for each pollutant-attributable and quantifiable health endpoint.

#### 2.3.1 PM<sub>2.5</sub>

The following sections of the 2019 PM ISA and 2022 PM ISA Supplement correspond to health endpoints judged as having a “causal” or “likely to be causal” relationship with PM<sub>2.5</sub> exposure, respectively:<sup>34</sup>

- 5.1 Short-Term PM<sub>2.5</sub> Exposure and Respiratory Effects,
- 5.2 Long-Term PM<sub>2.5</sub> Exposure and Respiratory Effects,
- 6.1 and 3.1 Short-Term PM<sub>2.5</sub> Exposure and Cardiovascular Effects,
- 6.2 and 3.1 Long-Term PM<sub>2.5</sub> Exposure and Cardiovascular Effects,
- 8.2 Long-Term PM<sub>2.5</sub> Exposure and Nervous System Effects,
- 10.2 [Long-Term] PM<sub>2.5</sub> Exposure and Cancer,
- 11.2 and 3.2 Long-Term PM<sub>2.5</sub> Exposure and Total Mortality

Following the approach to identifying available epidemiologic literature (section 2.2), we began with the 2,882 studies cited by the 2019 PM ISA or 2022 PM ISA Supplement ((U.S. EPA 2019, U.S. EPA 2022)). Of

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<sup>33</sup> As an example, we often cannot pool across hazard ratios reported in long-term exposure cohort studies. The challenges associated with synthesizing the results of long-term cohort studies have been described elsewhere (Burnett, R., H. Chen, M. Szyszkowicz, N. Fann, B. Hubbell, C. A. Pope, 3rd, J. S. Apte, M. Brauer, A. Cohen, S. Weichenthal, J. Coggins, Q. Di, B. Brunekreef, J. Frostad, S. S. Lim, H. Kan, K. D. Walker, G. D. Thurston, R. B. Hayes, C. C. Lim, M. C. Turner, M. Jerrett, D. Krewski, S. M. Gapstur, W. R. Diver, B. Ostro, D. Goldberg, D. L. Crouse, R. V. Martin, P. Peters, L. Pinault, M. Tjepkema, A. van Donkelaar, P. J. Villeneuve, A. B. Miller, P. Yin, M. Zhou, L. Wang, N. A. H. Janssen, M. Marra, R. W. Atkinson, H. Tsang, T. Quoc Thach, J. B. Cannon, R. T. Allen, J. E. Hart, F. Laden, G. Cesaroni, F. Forastiere, G. Weinmayr, A. Jaensch, G. Nagel, H. Concin and J. V. Spadaro (2018). "Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter." *Proc Natl Acad Sci U S A* **115**(38): 9592-9597.).

<sup>34</sup> Due to the cutoff date of the 2022 Supplement to the PM ISA (March 2021) and the recent and the evolving nature of the pandemic, we are unable to assess associations between PM<sub>2.5</sub> and COVID-19.

these, 559 studies evaluated mortality or morbidity health endpoints that the 2019 PM ISA determined as having a “causal” or “likely causal” relationship with PM<sub>2.5</sub> exposure and are clinically relevant (sections 2.2.1 and 2.2.2).<sup>35</sup> Of these, 150 studies met the minimum required criteria (section 2.1.1).<sup>36</sup>

We preferentially selected epidemiologic studies specifying ICD-9 or ICD-10 codes that reflected a broad array of adverse effects; the ISA reports that the evidence for these broader effects is stronger than it is for specific outcomes, helps avoid double-counting of health benefits across categories and is consistent recommendations from the EPA Science Advisory Board.<sup>37</sup> The remaining studies were sorted by health endpoint and PM<sub>2.5</sub> exposure relationship (i.e., short-term or long-term exposure to PM<sub>2.5</sub>). These studies included 16 unique health endpoints (Table 6). In Table 6, the number of available studies refers to the number of North American studies meeting the minimum required criteria within each health endpoint, and a single study may be relevant to multiple endpoints. The risk estimates from the different studies for each endpoint can either be pooled (section 2.2.4.1) or kept as separate estimates (section 2.2.4.2), the latter of which is more common for mortality endpoints. The two columns to the far left provide the number of available risk estimates from each included study, as well as the number of risk estimates to be pooled or kept separate for each endpoint.

Once the studies were grouped by health endpoint, we applied the preferred criteria to obtain the final set of studies to inform each health endpoint. For each of the 16 endpoints, we performed a study ranking process based on these criteria that emphasized characteristics in Table 2. When no new epidemiologic studies of health endpoints previously supported by the ISAs were available, the risk estimates used previously were brought forward (e.g., work loss days).

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<sup>35</sup> Mortality studies were treated slightly differently. More information is available in section 2.3.1.1.1.

<sup>36</sup> This number may not equal the sum of available studies in Table 6 as individual studies may present risk estimates for multiple health endpoints.

<sup>37</sup> The Health Effects Subcommittee (HES) of the Advisory Council on Clean Air Compliance Analysis (Council) provided recommendations on the distinction between specific diagnostic codes and broad health outcome categories in 2004 (Ostro, B. C., T. A. (2004). Letter from Dr. Bart Ostro, Chair, Health Effects Subcommittee and Dr. Trudy Ann Cameron, Chair, Advisory Council on Clean Air Compliance Analysis to Honorable Michael O. Leavitt, Administrator, US EPA. Re: Advisory on Plans for Health Effects Analysis in the Analytical Plan for EPA's Second Prospective Analysis - Benefits and Costs of the Clean Air Act, 1990-2020. M. Leavitt. U.S. EPA HQ, Washington DC, Office of the Administrator, Science Advisory Board.). The HES recommended “health outcome estimates that can be more closely linked to the results of epidemiologic studies. However, if in the efforts to achieve a match, the outcome specification is too narrow (e.g., “acute bronchitis” instead of “all respiratory conditions”), small numbers will seriously reduce the reliability of the analysis. Therefore, careful consideration of the diagnostic codes to use (with the related tradeoffs in uncertainty) will be an important step in constructing the baseline data sets.”

Table 6. PM<sub>2.5</sub> Study and Risk Estimate Identification Diagram\*

PM Endpoint and Exposure Duration	Studies Available	Studies Included	Ages	Risk Estimates Available	Risk Estimates Included
All-Cause Mortality (LT)	2	1	Infants	1	1
	35	3	Adults and older adults	115	1
			Older adults	70	1
Cardiovascular Hospital Admissions (ST)	15	1	Children, adults, and older adults	28	7
Cardiovascular Emergency Department Visits (ST)	2	1	Children, adults, and older adults	3	1
Acute Myocardial Infarction (ST)	1	1	Adults and older adults	4	1
Stroke (LT)	4	1	Older adults	1	1
Cardiac Arrest (ST)	3	3	Adults and older adults	12	1
				12	1
				7	1
Respiratory Hospital Admissions (ST)	12	2	Children	3	1
			Older adults	4	1
Respiratory Emergency Department Visits (ST)	10	1	Children	16	4
Asthma Onset (LT)	5	1	Children	7	1
Asthma Symptoms (ST)	8	1	Children	8	1
Allergic Rhinitis	1	1	Children	5	1
Minor Restricted Activity Days	NA	1	Adults and older adults	NA	1
Work Loss Days	NA	1	Adults and older adults	NA	1
Lung Cancer (LT)	4	1	Adults and older adults	24	1
Alzheimer's Disease (LT)	1	1	Older adults	53	1
Parkinson's Disease (LT)	3	1	Older adults	53	1

ST- short-term exposure; LT- long-term exposure; NA- not applicable due to the absence of recent available epidemiologic studies in the ISA; risk estimates identified in the 2012 PM NAAQS RIA will continue to be utilized.

\*See associated Study Information Table for specific study details.

### 2.3.1.1 All-Cause Mortality

The 2022 supplement to the PM ISA re-affirmed that a “causal” relationship exists between both long- and short-term PM<sub>2.5</sub> exposure and all-cause mortality ((U.S. EPA 2022)). Specifically, the 2022 supplement to the ISA states that:

*Recent epidemiologic studies published since the 2019 PM ISA support and extend the evidence that contributed to the conclusion of a causal relationship between long-term PM<sub>2.5</sub> exposure and cardiovascular effects. Numerous U.S. and Canadian cohort studies conducted in locations where the long-term PM<sub>2.5</sub> concentration are less than 13 µg/m<sup>3</sup> add to the strong evidence base that was characterized in the 2019 PM ISA describing the relationship between long-term PM<sub>2.5</sub> and cardiovascular mortality, and specifically IHD- and stroke-related mortality. Overall, these recent cardiovascular mortality studies reported positive associations at varying spatial scales and across different exposure assessment and statistical methods. The associations between long-term PM<sub>2.5</sub> exposure and cardiovascular mortality generally persisted in models that were adjusted for ozone, NO<sub>2</sub>, PM<sub>10-2.5</sub>, or SO<sub>2</sub>, and most analyses of the C-R function supported a linear, no-threshold relationship for cardiovascular mortality, especially at lower ambient concentrations of PM<sub>2.5</sub>*

The biological pathways by which short- and long term PM<sub>2.5</sub> exposures are understood to lead to health effects are quite similar (section 2.2.1.2.1) and so we assume that effects observed in studies of long-term exposures may also reflect the influence of short-term exposures. Therefore, only mortality impacts from long-term PM<sub>2.5</sub> exposure will be quantified, so as not to overestimate impacts. This may potentially bias long-term, all-cause PM<sub>2.5</sub>-attributable mortality impact estimates toward the null in the main benefit estimate.

Additional support for including estimates of all-cause PM<sub>2.5</sub> mortality, as opposed to cause-specific, comes from the recommendations of advisory boards and review panels. For example, in response to suggestions made in a 2002 National Resources Council (NRC) report, expert judgement studies of mortality impacts were conducted ((NRC 2002)). The report recommended that “the main quantitative question should focus on all-cause mortality as the outcome, rather than eliciting separate concentration-response functions for specific causes of death” ((IEc 2006)). Similarly, a more recent Health Effects Subcommittee (HES) of the Advisory Council on Clean Air Compliance Analysis (Council) affirmed the inclusion of all-cause long-term PM<sub>2.5</sub> estimate with no threshold was “sound” ((Hammitt and Bailar 2010)).

#### 2.3.1.1.1 Available Epidemiologic Literature

Whereas for all other health endpoints we began by identifying North American epidemiologic studies from the relevant ISA ((U.S. EPA 2019), Figures 11-17 and 11-18), available literature for this health endpoint had been further reviewed by EPA in the 2022 PM Policy Assessment (PA) ((U.S. EPA 2022) sections 3.3 and Figure 3-4). As part of this review, the PA identified multi-city studies and more recent reanalysis or extensions of some of the commonly used cohorts. As such, for this health endpoint we began with the 35 epidemiologic multi-city cohort studies identified in the 2022 PM PA, which all met the minimum criteria and accounts for studies identified in the supplement to the PM ISA ((U.S. EPA 2022), section 2.1.1).

We separately evaluated the more limited literature available regarding PM<sub>2.5</sub>-attributable infant mortality (ages 0-12 months) cited in the 2009 ISA, as no more recent studies of PM<sub>2.5</sub>-attributable all-cause infant mortality were available in either the 2019 ISA or the 2022 supplement to the PM ISA. Full study information can be found in the Study Information Table (section 2.2.3).

#### 2.3.1.1.2 Identifying Suitable Studies for Use in Benefits Assessments

The systematic identification criteria (section 0) was applied to the 35 studies of PM<sub>2.5</sub>-attributable long-term all-cause mortality in adults, which prioritized particularly germane attributes including geographic coverage, population representativeness, and method of exposure estimation. As it is not relevant to study identification, we did not consider the risk effect magnitude as a criterion for study identification.

The 35 studies varied considerably with regards to all criteria considered. For example, study sizes ranged from the thousands to the tens of millions. Ultimately, all preferred criteria relevant to PM<sub>2.5</sub> factored into the identification of the studies best characterizing risk across the country, although geographic diversity, exposure estimation technique, population attributes, PM<sub>2.5</sub> concentrations, and inclusion of the copollutant O<sub>3</sub> were particularly germane. Specific information can be found in the corresponding Study Information Table.

#### 2.3.1.1.3 Studies and Risk Estimates Identified as Most Suitable for Use in Benefits Assessments

We select multiple cohort risk estimates to estimate counts of PM-related premature death, following an approach employed in previous RIAs (e.g., (U.S. EPA 2011, U.S. EPA 2011, U.S. EPA 2011, U.S. EPA 2012, U.S. EPA 2012, U.S. EPA 2015, U.S. EPA 2019)). Quantifying effects using risk estimates reported in alternative cohorts helps account for uncertainty in the estimated number of PM-related premature deaths.

The systematic approach led us to identify three studies best characterizing risk across the U.S. ((Turner, Jerrett et al. 2016, Pope III, Lefler et al. 2019, Wu, Braun et al. 2020)).<sup>38,39</sup> These three studies used data from three cohorts, an analysis of Medicare beneficiaries (Medicare), the American Cancer Society (ACS) and the National Health Interview Survey (NHIS). The supplement to the PM ISA concluded that the NHIS Medicare cohorts provide strong evidence of the association between long-term PM<sub>2.5</sub> exposure and mortality with support from several additional cohort studies ((U.S. EPA 2019, U.S. EPA 2022)). We discuss uncertainty and sensitivity considerations related to the identified mortality risk estimates in sections 6.1.2 and 6.5.<sup>40</sup>

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<sup>38</sup> The 2020 and 2022 PM PAs cited a number of relative advantages of these studies related to the extended period of observation, the rigorous examination of model forms and effect estimates, the coverage for ecological variables, and the large dataset with regards to both population and area (U.S. EPA (2019). Integrated Science Assessment (ISA) for Particulate Matter (Final Report). U. S. EPA. Research Triangle Park, NC, U.S. Environmental Protection Agency, Office of Research and Development, Center for Public Health and Environmental Assessment, U.S. EPA (2022). Policy Assessment for the Reconsideration of the National Ambient Air Quality Standards for Particulate Matter (Final Report). U. S. EPA. Research Triangle Park, NC, U.S. Environmental Protection Agency, Office of Air Quality Planning and Standards, Health and Environmental Impacts Division.).

<sup>39</sup> The Harvard Six Cities Study, which had been identified for use in estimating mortality impacts in the 2012 PM NAAQS RIA, was not identified using this approach due to geographic limitations (U.S. EPA (2012). Regulatory Impact Analysis for the Final Revisions to the National Ambient Air Quality Standards for Particulate Matter. U. S. EPA. Research Triangle Park, NC, U.S. Environmental Protection Agency, Office of Air Quality Planning and Standards, Health and Environmental Impact Division.).

<sup>40</sup> There are several other assumptions implicit in the calculation of PM<sub>2.5</sub>-related mortality impacts. Briefly, these include 1) an assumption of “cessation” lag in time between the reduction in PM exposure and the full reduction in mortality risk that affects the timing (and thus discounted monetary valuation) of the resulting deaths, 2) following conclusions of U.S. EPA (2019). Integrated Science Assessment (ISA) for Particulate Matter (Final Report). U. S. EPA. Research Triangle Park, NC, U.S. Environmental Protection Agency, Office of Research and Development, Center

### 2.3.1.1.3.1 Adult Mortality

#### 2.3.1.1.3.1.1 NHIS

(Pope III, Lefler et al. 2019) constructed a cohort using a survey of 1,599,329 U.S. adults (aged 18-84 years) who were interviewed in the National Health Interview Surveys (NHIS) between 1986 and 2014 and linked to the National Death Index (NDI) through 2015. The authors then performed survival modeling in this cohort to examine the relationship between long-term PM<sub>2.5</sub> exposure and all-cause mortality. The authors also constructed a subcohort of 635,539 adults from the full cohort for whom body mass index (BMI) and smoking status data were available. The authors employed a hybrid modeling technique to estimate annual-average PM<sub>2.5</sub> concentrations derived from regulatory monitoring data and constructed in a universal kriging framework using geographic variables including land use, population, and satellite estimates. (Pope III, Lefler et al. 2019) assigned annual-average PM<sub>2.5</sub> exposure from 1999-2015 to each individual by census tract and utilized complex (accounting for NHIS's sample design) and simple Cox proportional hazards models for the full cohort and the subcohort. We select the Hazard Ratio calculated using the complex model for the subcohort, which controls for individual-level covariates including age, sex, race-ethnicity, inflation-adjusted income, education level, marital status, rural versus urban, region, survey year, BMI, and smoking status. In a single-pollutant model, the coefficient and standard error for PM<sub>2.5</sub> are estimated from the hazard ratio (1.12) and 95% confidence interval (1.08-1.15) associated with a change in annual mean PM<sub>2.5</sub> exposure of 10 ug/m<sup>3</sup> (Pope et al. 2019, Table 2, Subcohort).

#### 2.3.1.1.3.1.2 Medicare

(Wu, Braun et al. 2020) evaluated the relationship between long-term PM<sub>2.5</sub> exposure and all-cause mortality in more than 68.5 million Medicare enrollees (over the age of 64), using Medicare claims data from 2000-2016 representing over 573 million person-years of follow-up and over 27 million deaths. This cohort included over 20% of the U.S. population and was, at the time of publishing, the largest air pollution study cohort to date. The authors modeled PM<sub>2.5</sub> exposure at a 1-km<sup>2</sup> grid resolution using a hybrid ensemble-based prediction model that combined three machine learning models and relied on satellite data, land-use information, weather variables, chemical transport model simulation outputs, and monitor data. (Wu, Braun et al. 2020) fit five different statistical models: a Cox proportional hazards model, a Poisson regression model, and three causal inference approaches (GPS estimation, GPS matching, and GPS weighting). All five statistical approaches provided consistent results; we report the results of the Cox proportional hazards model here. The authors adjusted for numerous individual-level and community-level confounders, and sensitivity analyses suggest that the results are robust to unmeasured confounding bias. In a single-pollutant model, the coefficient and standard error for PM<sub>2.5</sub> are estimated from the hazard ratio (1.066) and 95% confidence interval (1.058-1.074) associated with a change in annual mean PM<sub>2.5</sub> exposure of 10.0 ug/m<sup>3</sup> ((Wu, Braun et al. 2020), Table S3, Main analysis, 2000-2016 Cohort, Cox PH).

#### 2.3.1.1.3.1.3 American Cancer Society

Two independent studies evaluated the same years of data from the large, nationwide ACS CSP-II cohort of those > 29 years old ((Turner, Jerrett et al. 2016, Pope III, Lefler et al. 2019)). These studies extended

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for Public Health and Environmental Assessment., we assume that all fine particles are equally potent in causing mortality, and 3) following conclusions of the *ibid.*, we assume that the health impact function for fine particles is linear within the range of ambient concentrations affected by these standards.

the follow-up period of the ACS CSP-II to 22 years (1982-2004), evaluating 669,046 participants over 12,662,562 person-years of follow up and 237,201 observed deaths. These two studies applied a more advanced exposure estimation approach than had previously been used when analyzing the ACS cohort, combining the geostatistical Bayesian Maximum Entropy framework with national-level land use regression models.

In addition to adjusting for individual-level and ecological covariates, (Turner, Jerrett et al. 2016) also controlled for occupational PM<sub>2.5</sub> exposure and adjusted for the potential copollutants O<sub>3</sub> and nitrogen dioxide. Although the copollutant adjustment did not significantly change the hazard ratio, similar to the risk assessment performed as part of the PM PA ((U.S. EPA 2022)), we identified it as the most suitable hazard ratio when estimating health benefit impacts. Thus, the total mortality risk estimate is based on the random-effects Cox proportional hazard model that incorporates multiple individual and ecological covariates (relative risk =1.06, 95% confidence intervals 1.04–1.08 per 10µg/m<sup>3</sup> increase in PM<sub>2.5</sub>). The relative risk estimate is identical to a risk estimate drawn from earlier ACS analysis of all-cause long-term exposure PM<sub>2.5</sub>-attributable mortality ((Krewski, Jerrett et al. 2009)). Of note, the ACS cohort participants were recruited by approximately 77,000 ACS volunteers and may not precisely represent the overall U.S. population demographics.

#### *2.3.1.1.3.1.4 Summary*

Based on the 2019 PM ISA, EPA has used two estimates of mortality: one from the American Cancer Society cohort and one from the Medicare cohort ((Turner, Jerrett et al. 2016) and (Di, Wang et al. 2017), respectively). We use a risk estimate from (Pope III, Lefler et al. 2019) study in place of the risk estimate from the ((Turner, Jerrett et al. 2016) analysis, as it: (1) includes a longer follow-up period that includes more recent (and lower) PM<sub>2.5</sub> concentrations; (2) the NHIS cohort is more representative of the U.S. population than is the ACS cohort with respect to the distribution of individuals by race, ethnicity, income and education.

Based on the 2020 Supplement to the PM ISA, EPA substituted a risk estimate from (Wu, Braun et al. 2020) in place of a risk estimate from (Di, Wang et al. 2017). These two epidemiologic studies share many attributes, including the cohort and model used to characterize population exposure to PM<sub>2.5</sub>. As compared to (Di, Wang et al. 2017), (Wu, Braun et al. 2020) includes a longer follow-up period and reflects more recent PM<sub>2.5</sub> concentrations.

#### *2.3.1.1.3.2 Infant Mortality*

In addition to the adult mortality studies described above, several studies show an association between PM exposure and mortality in children under 5 years of age ((U.S. EPA 2009)).<sup>41</sup> The 2019 PM ISA concluded that evidence exists for a stronger effect at the post neonatal period and for respiratory-related mortality, although this trend is not consistent across all studies. The supplement to the PM ISA did not identify any new studies characterizing PM exposure and mortality among children ((U.S. EPA 2022)).

Although the ISA evidence supports a relationship between PM<sub>2.5</sub> exposure and death in children, only studies of infant mortality met the minimum criteria (section 2.1.1). Previously, EPA has included estimates of post neonatal infant mortality from (Woodruff, Grillo et al. 1997) ((U.S. EPA 2012, U.S. EPA

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<sup>41</sup> For the purposes of this analysis, we only calculate benefits for infants aged 0–12 months, not all children under 5 years old.



2019)). As such, compared to avoided deaths estimated for adult mortality, avoided deaths for infants are significantly smaller due to the size of the population and the smaller risk estimates associated with exposure to PM from epidemiology studies on infant mortality.

In a more recent study including a larger and more nationally-representative study size by the same group, authors examined the relationship between long-term exposure to fine PM<sub>2.5</sub> air pollution and post neonatal infant mortality in 3,583,495 births from 96 counties containing >249,999 residents across the U.S. between 1999-2002 using data from the National Center for Health Statistics ((Woodruff, Darrow et al. 2008)). They linked average PM<sub>2.5</sub> monitoring data over the first two months of life with 6,639 post neonatal deaths, using logistic regression that incorporated generalized estimating equations (GEE) to estimate the odds ratios for all-cause and cause-specific post neonatal mortality by exposure to air pollution.<sup>42</sup> The study population experienced a median PM<sub>2.5</sub> concentration of 14.8 µg/m<sup>3</sup>, with 25% of the population experiencing concentrations below 12 µg/m<sup>3</sup> and above 18.8 µg/m<sup>3</sup>. The study included an evaluation of the appropriateness of a linear form from analysis based on quartiles of exposure and determined the linear form as a reasonable assumption. Study results included a single risk estimate of PM<sub>2.5</sub>-attributable all-cause mortality, 1.04 (0.98-1.11) per 7 µg/m<sup>3</sup> (interquartile range) increase in PM<sub>2.5</sub>.

### 2.3.1.2 Cardiovascular Hospital Admissions

The ISA found “generally consistent, positive associations observed in numerous epidemiologic studies of emergency department visits and hospital admissions for ischemic heart disease, heart failure, and combined cardiovascular-related endpoints” ((U.S. EPA 2019), section 6.1.16). Also, the ISA calls out cardiovascular hospital admissions as a population level health endpoint related to short-term PM<sub>2.5</sub> exposure (section 2.2.1.2.1.1).

#### 2.3.1.2.1 Available Epidemiologic Literature

Fifteen North American epidemiologic studies of cardiovascular hospital admissions<sup>43</sup> were identified in section 6.1 of the PM ISA ((U.S. EPA 2019)) and in the Supplement to the PM ISA ((U.S. EPA 2019, U.S. EPA 2022)). Relevant information related to the identification criteria, including study location, population attributes, and study period, were extracted from the studies and is available in the associated Study Information Table. The hospital admissions endpoint reports the number of events, as opposed to the number of individuals who experienced the event.

#### 2.3.1.2.2 Identifying Suitable Studies for Use in Benefits Assessments

Relevant study information was used to identify the most nationally representative study or studies available. Study details can be found in the associated Study Information Table. The available cardiovascular hospital admissions studies predominantly included locations across the contiguous U.S. and evaluated the Medicare cohort, although two studies evaluated all ages. Few studies included health or air quality data post-2006, used hybrid exposure estimation techniques, or included O<sub>3</sub> as a copollutant in the risk estimates. Importantly, while all studies assessed a broad range of cardiovascular effects, the specific ICD codes included varied widely. Of the available studies, (Bell, Son et al. 2015) evaluated the most recent study period and included the most nationally representative study locations.

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<sup>42</sup> Odds ratios are a subtype of risk estimates.

<sup>43</sup> Of the ~35 million annual hospital discharges, ~20% are related to cardiovascular effects, ~10% to respiratory effects, and ~2% to nervous system effects (<https://www.cdc.gov/nchs/data/nhsr/nhsr029.pdf>).

2.3.1.2.3 Studies and Risk Estimates Identified as Most Suitable for Use in Benefits Assessments (Bell, Son et al. 2015) investigated the effects of short-term fine particulate matter (PM<sub>2.5</sub>) exposure on cardiovascular health (ICD-9 410, omitting 410.x2; 410-414; 426-427; 428; 429; 430-438; and 440-448). Authors acquired data for 213 U.S. counties (1999-2010) from the Medicare Claims Inpatient Files for U.S. residents >65 years of age. Authors chose variables including sex, age, county of residence, and cause of hospital admission, as determined by ICD-9 codes. Authors collected PM<sub>2.5</sub> exposure data from county population-based ambient monitors from the US EPA Air Quality System and averaged for county and day. Data were present for 56.5% of study days. (Bell, Son et al. 2015) utilized Bayesian hierarchical modeling to examine the links between PM<sub>2.5</sub> and hospital admissions, running separate models to generate risk models for time lags (0-2 days) and season for any estimated variation in health effects. The percent increase in risk of 0.65% (95% CI: 0.48-0.83) for an increase of 10 µg/m<sup>3</sup> in same-day daily mean PM<sub>2.5</sub> concentrations came from a single pollutant model.

### 2.3.1.3 Cardiovascular Emergency Department Visits

The ISA found that “generally consistent, positive associations observed in numerous epidemiologic studies of emergency department visits and hospital admissions for ischemic heart disease, heart failure, and combined cardiovascular-related endpoints” ((U.S. EPA 2019) section 6.1.16). The ISA also calls out cardiovascular emergency department visits as a population level health endpoint related to short-term PM<sub>2.5</sub> exposure (section 2.2.1.2.1.1).

#### 2.3.1.3.1 Available Epidemiologic Literature

Although there were several studies of both emergency department visits and hospital admissions, there was only one short-term exposure epidemiologic study specific to cardiovascular emergency department visits available in the 2019 PM ISA ((U.S. EPA 2019)).

2.3.1.3.2 Study and Risk Estimates Identified as Most Suitable for Use in Benefits Assessments (Ostro, Malig et al. 2016) investigated the association between short-term, source-specific (vehicular emissions, biomass burning, soil, and secondary NO<sub>3</sub> and SO<sub>4</sub> sources) PM<sub>2.5</sub> concentrations and emergency department visits for respiratory and cardiovascular diseases in eight cities in California from 2005 to 2008. Authors obtained medical and demographic data from the Office of Statewide Health Planning and Development in California, and diagnosis was defined with ICD-9 codes: all cardiovascular (390-459), ischemic heart disease (410–414), AMI (410), cardiac dysrhythmia (427), and heart failure (428). (Ostro, Malig et al. 2016) conducted a case cross-over analysis, stratified by year and month, controlling for weather and day of the week covariates. Authors used a county-level logistic regression and random-effects meta-analysis to examine the association between source-specific PM<sub>2.5</sub> and emergency department visits for respiratory and cardiovascular diseases. Results indicate a positive association between vehicle PM<sub>2.5</sub> emissions and emergency department visits for all cardiovascular diseases. The identified excess risk estimate of 0.7% (95% CI: -0.2-1.7) per 11.4 µg/m<sup>3</sup> (interquartile range) daily mean PM<sub>2.5</sub> concentration increase came from a single pollutant model lagged by 2 days.

#### 2.3.1.4 Cardiac Arrest (Out-of-Hospital)

The 2019 PM ISA stated that “in contrast to the studies from the previous review, recent studies have reported generally positive associations between short-term PM<sub>2.5</sub> exposure and out-of-hospital cardiac arrest” ((U.S. EPA 2019), section 6.1). The ISA also called out conductance abnormalities as a key clinical effect associated with both short-and long-term PM<sub>2.5</sub> exposures (section 2.2.1.2.1.1).

This endpoint, like several others (e.g., lung cancer incidence, section 2.3.1.14) has a very high rate of fatality. As mortality due to any cause is captured separately (section 2.3.1.1), we focus on impacts following cardiac arrest, in the population that survive the initial event when considering this health endpoint.<sup>44</sup>

#### 2.3.1.4.1 Available Epidemiologic Literature

The 2019 PM ISA included three epidemiologic studies of out-of-hospital cardiac arrest that met our minimum identification criteria ((U.S. EPA 2019), section 2.1.1).

#### 2.3.1.4.2 Identifying Suitable Studies for Use in Benefits Assessments

All three studies each evaluated separate locations and were similar with regards to study aspects such as age range ((Rosenthal, Carney et al. 2008, Silverman, Ito et al. 2010, Ensor, Raun et al. 2013)). Due to differences only in the study period and locations, the three studies are pooled using the random or fixed effects pooling method for benefits assessment purposes.<sup>45</sup>

#### 2.3.1.4.3 Studies and Risk Estimates Identified as Most Suitable for Use in Benefits Assessments

(Ensor, Raun et al. 2013) studied the association between short-term ambient air pollution (PM<sub>2.5</sub> and O<sub>3</sub>) exposure and out-of-hospital cardiac arrest. (Ensor, Raun et al. 2013) gathered medical and demographic data from an Emergency Medical Services database in Houston, Texas between 2004 and 2011. Authors assessed the medical data and defined out-of-hospital cardiac arrest as emergency medical services performing chest compressions. Authors collected ambient air pollution and weather data from Texas Commission of Environmental Quality monitors and calculated hourly and daily averages for PM<sub>2.5</sub> and O<sub>3</sub>. The authors used a time-stratified case crossover analysis and conditional logistic regression to interpret the data and found that with a daily increase of 6 µg/m<sup>3</sup> in PM<sub>2.5</sub>, averaged from a 0- and 1-day lag, there was an increased risk of out-of-hospital cardiac arrest of 3.9% (95% CI: 0.5-7.4).

(Silverman, Ito et al. 2010) investigated the link between short-term ambient air pollution exposure (PM<sub>2.5</sub>, NO<sub>2</sub>, SO<sub>2</sub>, O<sub>3</sub>, and CO) and out-of-hospital cardiac arrest in New York City between 2002 and 2006. Authors obtained medical data from the Emergency Medical Services of the New York City Fire Department for 8,216 subjects aged 0 to 99, average age 65.6 with slightly more men than women. Authors collected air pollution and weather data from the US EPA's Air Quality System monitors within a 20-mile radius of New York City and averaged over 24-hour periods. Authors conducted time series and case crossover analyses with 0- and 1-day lagged air pollution levels and by season. (Silverman, Ito et al. 2010) found that in a single-pollutant case crossover model, each 10 µg/m<sup>3</sup> increase in ambient PM<sub>2.5</sub>

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<sup>44</sup> Similarly, as any emergency department visits or hospital admissions resulting from cardiac arrest would be included in other endpoints (sections 2.3.1.2 and 2.3.1.3), monetized benefits of this health endpoint would not include and emergency department visits or hospital admissions costs.

<sup>45</sup> Random or fixed effects pooling is a method to combine two or more distributions into a single new distribution, allowing for the possibilities that either 1) a single true underlying relationship exists between the component distributions, and that differences among estimated parameters are the result of sampling error, or 2) the estimated parameter from different studies may in fact be estimates of different parameters, rather than just different estimates of a single underlying parameter, and weights for the pooling are generated via inverse variance weighting, thus giving more weight to the studies that exhibit lower variance and less weight to the input distributions with higher variance.

resulted in a relative risk of 1.04 (95% CI: 0.99-1.08) in out-of-hospital cardiac arrest incidences 0- and 1-day prior to onset.

(Rosenthal, Carney et al. 2008) examined the effects of short-term PM<sub>2.5</sub> exposure on out-of-hospital cardiac arrest incidence and whether these effects were connected to demographic data or presence of heart rhythm. Additionally, (Rosenthal, Carney et al. 2008) compared exposure time and measurement method on the effects of short-term PM<sub>2.5</sub> exposure and out-of-hospital cardiac arrest incidence. Authors obtained medical data from the Wishard Ambulance Service, a local emergency medical service in Indianapolis, Indiana, from July 2, 2002 to July 7, 2006. The study defined out-of-hospital cardiac arrest using the same criteria as (Ensor, Raun et al. 2013) and (Silverman, Ito et al. 2010). Authors collected daily and hourly PM<sub>2.5</sub> concentrations from two City of Indianapolis monitoring sites and using two separate methods: the Federal Reference Method (FRM) for 24-hour filter samples, and a Federal Equivalence Method (FEM). The authors used a case crossover analysis with conditional logistic regressions in order to study the effects of short-term PM<sub>2.5</sub> exposure on out-of-hospital cardiac arrest incidence. (Rosenthal, Carney et al. 2008) found a positive but statistically insignificant association between non-dead on arrival (non-DOA) out-of-hospital cardiac arrest cases and ambient PM<sub>2.5</sub> concentrations. Although they also noted a statistically significant positive association when restricted to witnessed, non-DOA out-of-hospital cardiac arrest cases, that subgroup is less applicable to the available baseline incidence rate of non-DOA out-of-hospital cardiac arrest cases. The identified risk estimate of 1.02 (95% CI: 0.92-1.12) for each 10 µg/m<sup>3</sup> increase in daily mean PM<sub>2.5</sub> concentrations lagged by 0-1 days, came from a single-pollutant model of all non-DOA out-of-hospital cardiac arrest cases.

### 2.3.1.5 Acute Myocardial Infarctions (AMI)

The 2019 PM ISA found that “evidence from the current review strengthens the epidemiologic results reported in the 2009 PM ISA” with respect to AMI ((U.S. EPA 2019)). In addition, the 2022 Supplement to the 2019 PM ISA stated:

*Studies examining short-term PM<sub>2.5</sub> exposure report consistent positive associations for cardiovascular-related emergency department (ED) visits and hospital admissions, specifically for...myocardial infarction (MI). ... The epidemiologic studies reviewed in the 2019 PM ISA strengthened the evidence characterized in the previous ISA (U.S. EPA, 2009). Most of the evidence for IHD and MI in the 2009 PM ISA was from multicity epidemiologic studies of ED visits and hospital admissions [i.e., the U.S. Medicare Cohort Air Pollution Study (MCAPS) (Dominici et al., 2006), a four-city study in Australia (Barnett et al., 2006), and a study among older adults in several French cities (Host et al., 2008)]. The positive associations reported in these studies were an important line of evidence in the 2009 PM ISA concluding a causal relationship between short-term PM<sub>2.5</sub> exposure and cardiovascular effects. Uncertainties noted in the 2009 PM ISA with respect to exposure measurement error for those not living near a PM<sub>2.5</sub> monitor were reduced in the 2019 PM ISA with the consideration of studies that applied hybrid exposure assessment techniques that combine land use regression data with satellite aerosol optical depth (AOD) measurements and PM<sub>2.5</sub> concentrations measured at fixed-site monitors to estimate PM<sub>2.5</sub> concentrations. Further, compared with the 2009 PM ISA, the evidence in the 2019 PM ISA was expanded to include studies examining the association of short-term PM<sub>2.5</sub> exposure ST segment depression in addition to ED visits and hospital admissions for MI. ... Overall, recent studies*

*support and extend the findings of the 2019 PM ISA with additional studies reporting positive associations between short-term PM<sub>2.5</sub> exposure and...MI hospital admissions and ED visits ((U.S. EPA 2022)).*

#### 2.3.1.5.1 Available Epidemiologic Literature

The 2019 PM ISA identified epidemiologic studies associating AMIs with short-term PM<sub>2.5</sub> exposures, though the studies passing the initial screening stage were not more suitable than those currently used to estimate benefits ((U.S. EPA 2019)). The Supplement to the ISA identified a single suitable short-term exposure study that passed the screening stage ((U.S. EPA 2022)).<sup>46</sup>

#### 2.3.1.5.2 Studies and Risk Estimates Identified as Most Suitable for Use in Benefits Assessments

The supplement to the PM ISA identified a single new epidemiologic study examining the relationship between short-term PM exposure and AMI ((U.S. EPA 2022)). (Wei, Wang et al. 2019) evaluated the relationship between short-term PM<sub>2.5</sub> exposure and hospital admissions for 214 mutually exclusive disease groups, including acute myocardial infarction, in a time-stratified, case-crossover analysis of over 95 million Medicare inpatient hospital claims from 2000-2012. The authors estimated daily PM<sub>2.5</sub> levels at a 1-km<sup>2</sup> grid cell level using a satellite based, neural network model that was calibrated using monitor data and assigned 0-1 day lagged PM<sub>2.5</sub> exposure to each participant by zip code of residence. For each disease group, (Wei, Wang et al. 2019) created a case crossover dataset that controlled for individual level and zip code level variables, day of the week, seasonality, and long-term time trends. The authors used conditional logistic regression models to estimate associations between PM<sub>2.5</sub> exposure and risk of hospital admission and found positive associations for numerous rarely studied and numerous well-studied disease groups. In a single-pollutant model, the coefficient and standard error are estimated from a reported relative increase in risk (0.11%) and 95% confidence interval (0.07%-0.16%) associated with a 1 ug/m<sup>3</sup> increase in 0-1 day lagged PM<sub>2.5</sub> exposure ((Wei, Wang et al. 2019), Figure 3, CCS 100 AMI). We thus based our estimates of AMI incidence on this study, assuming that all AMI were associated with a hospital admission.

### 2.3.1.6 Stroke

#### 2.3.1.6.1 Available Epidemiologic Literature

The 2019 PM ISA included three epidemiologic studies of stroke that met the minimum identification criteria ((U.S. EPA 2019), section 2.1.1).

#### 2.3.1.6.2 Identifying Suitable Studies for Use in Benefits Assessments

One of the available epidemiologic studies was more recent, included a larger population, evaluated long-term exposure effects, and was more representative of the U.S. with regards to both geography and population attributes than the other two studies ((Kloog, Coull et al. 2012)).

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<sup>46</sup> Five long-term exposure studies evaluated associations between PM<sub>2.5</sub> and AMI, however the Supplement to the PM ISA stated that “evidence informing the relationship between long-term exposure to PM<sub>2.5</sub> and IHD, including the recent studies of MI, ... do not all report positive associations; however, the strongest evidence of a relationship continues to be for those with preexisting diseases or patient populations that are followed after a cardiac event or procedure such as catheterization.” Due to the strength of the evidence, AMI associated with long-term PM<sub>2.5</sub> exposures was not included as a health endpoint.

2.3.1.6.3 Studies and Risk Estimates Identified as Most Suitable for Use in Benefits Assessments (Kloog, Coull et al. 2012) analyzed the effects of long- and short-term PM<sub>2.5</sub> exposure on hospital admissions due to strokes with a new PM<sub>2.5</sub> exposure model in New England (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont) from 2000 to 2006. We use this endpoint as a surrogate for PM<sub>2.5</sub>-attributable stroke incidence. Authors collected medical data from 67,678 adults aged 65 to 99 in the U.S. Medicare program database from 2000 to 2006. They defined all respiratory, cardiovascular disease, stroke, and diabetes based on emergency department visits and primary discharge diagnosis records. Authors used a hybrid exposure technique comprised of daily PM<sub>2.5</sub> concentration data from aerosol optical depth (AOD) measurements and ambient air monitors from the U.S. EPA and Interagency Monitoring of Protected Visual Improvements (IMPROVE). Authors also obtained land use regressions, meteorological data (National Climatic Data Center), and socioeconomic data (U.S. Census Bureau) matched to zip codes. Utilizing land use Poisson regression single-pollutant models, the authors found an 3.49% (95% CI: 0.09-5.18) increase in stroke incidence for a 10 µg/m<sup>3</sup> increase in the 7-year mean PM<sub>2.5</sub> concentrations.

#### 2.3.1.7 Respiratory Hospital Admissions

After considering the relationships between specific and broad respiratory hospital admissions endpoints, the 2019 PM ISA stated that “recent studies further expand analyses with older adults, with multicity studies conducted in the U.S. providing evidence of consistent, positive associations between short-term PM<sub>2.5</sub> exposure and respiratory-related diseases” ((U.S. EPA 2019), section 5.1.6).

The ISA noted that “it is often difficult to determine whether the associations observed indicate that PM<sub>2.5</sub> may affect the spectrum of respiratory diseases or reflects the evidence supporting associations with specific respiratory diseases, such as asthma.” Taking this into consideration, hospital admissions for asthma exacerbation/symptoms, COPD, and respiratory infections were specifically called out in the short-term PM<sub>2.5</sub> exposure biological plausibility diagram (section 2.2.1.2.1.2).

##### 2.3.1.7.1 Available Epidemiologic Literature

Like the cardiovascular hospital admission/emergency department visit endpoints, several respiratory studies identified by the ISA combined the hospital admissions and emergency department endpoints. There was also a subset of studies that only considered emergency hospital admission, defined as hospital admissions that originated in the emergency department. As using either studies of emergency hospital admissions or combined emergency department and hospital admission studies would result in increased uncertainty around the economic estimate and/or with the baseline incidence data, we limited our pool of available studies to those specifically evaluating unplanned respiratory hospital admissions, of which there were 12 available studies.

##### 2.3.1.7.2 Identifying Suitable Studies for Use in Benefits Assessments

Studies for this endpoint tended to focus on specific age groups, with approximately half focusing on older adults (>64) and none specifying ages 19-64. Importantly, studies varied widely by ICD codes, making pooling of two or more studies difficult. Considering the preferred criteria, two studies were identified, one of children and one of older adults, primarily due to the inclusion of diverse and large study locations. The single study of older adults is more informative than pooling it with other studies of the same population as it is more recent and includes exposure to lower PM<sub>2.5</sub> concentration levels.

2.3.1.7.3 Studies and Risk Estimates Identified as Most Suitable for Use in Benefits Assessments (Bell, Son et al. 2015) investigated the effects of short-term fine particulate matter (PM<sub>2.5</sub>) exposure on respiratory health (ICD-9 464-466, 480-487, 490-492, 493) in older adults (>64 years). Authors acquired data for 213 U.S. counties (1999-2010) from the Medicare Claims Inpatient Files for U.S. residents >65 years of age. Authors chose variables including sex, age, county of residence, and cause of hospital admission, as determined by ICD-9 codes. Authors collected PM<sub>2.5</sub> exposure data from county population-based ambient monitors from the US EPA Air Quality System and averaged for county and day. Data were present for 56.5% of study days due to the sampling schedule of the monitors. (Bell, Son et al. 2015) utilized Bayesian hierarchical modeling to examine the links between PM<sub>2.5</sub> and hospital admissions. They ran separate models for time lags (0-2 days) and season to determine if there were any estimated variation in health effects. The identified percent increase in risk of 0.25% (95% CI: 0.01-0.48) for an increase of 10 µg/m<sup>3</sup> in same-day daily mean PM<sub>2.5</sub> concentrations came from a single-pollutant model.

(Ostro, Roth et al. 2009) estimated the association between ambient PM<sub>2.5</sub>, EC, organic carbon (OC), NO<sub>3</sub>, and SO<sub>4</sub> on hospital admissions for respiratory diseases in children ages 5 to 19. The study used the California Office of Statewide Health Planning and Development, Healthcare Quality and Analysis Division hospitalization data from six California counties for the 2000 to 2003 study period. (Ostro, Roth et al. 2009) classified hospital admissions into: all respiratory disease (ICD-9 codes 460-519), asthma (ICD-9 code 493), acute bronchitis (ICD-9 code 466), and pneumonia (ICD-9 codes 480-486). They aggregated the hospital admission data to the county level to create a daily time series of admissions for each county. Authors took air quality measurements from the California Air Resources Board, which captured speciated 24-hour average pollutant measurements using a filter-based Met One Speciation Air Sampling System. Meteorological measurements for average daily temperature and relative humidity came from the California Air Resources Board or the California Irrigation Management Information System. Authors analyzed data using a Poisson regression with time, day of the week, temperature, relative humidity, and pollutant as explanatory variables. (Ostro, Roth et al. 2009) controlled for seasonality and time dependent effects by including a natural spline smoother for the daily time trend and meteorology. The identified percent increase in risk of excess risk of 4.1% (95% CI: 1.8-6.4) for a 14.6 µg/m<sup>3</sup> increase in daily mean PM<sub>2.5</sub> concentrations, lagged by 3 days, came from a single-pollutant model.

#### 2.3.1.8 Respiratory Emergency Department Visits

After considering the relationships between specific and broad respiratory emergency department visit endpoints, the 2019 PM ISA stated that “recent studies further expand analyses with older adults, with multicity studies conducted in the U.S. providing evidence of consistent, positive associations between short-term PM<sub>2.5</sub> exposure and respiratory-related diseases” ((U.S. EPA 2019), section 5.1.6).

The ISA noted that “it is often difficult to determine whether the associations observed indicate that PM<sub>2.5</sub> may affect the spectrum of respiratory diseases or reflects the evidence supporting associations with specific respiratory diseases, such as asthma.” Emergency department visits for asthma exacerbation/symptoms, COPD, and respiratory infections were specifically called out in the short-term PM<sub>2.5</sub> exposure biological plausibility diagram (section 2.2.1.2.1.2).

#### 2.3.1.8.1 Available Epidemiologic Literature

Like the cardiovascular hospital admission/emergency department visit endpoints, several respiratory studies identified by the ISA combined the hospital admissions and emergency department endpoints. As using the combined study endpoint would result in increased uncertainty around the economic estimate, we limited our pool of available studies to those specifically looking at respiratory emergency department visits for the main benefits assessment, of which there were 10 studies.

#### 2.3.1.8.2 Identifying Suitable Studies for Use in Benefits Assessments

One study out of the 10 was more recent, provided greater geographic representation, and included all ages.

#### 2.3.1.8.3 Studies and Risk Estimates Identified as Most Suitable for Use in Benefits Assessments

(Krall, Anderson et al. 2013) investigated the associations between short-term, source-specific (traffic and coal combustion) ambient PM<sub>2.5</sub> exposure and emergency department visits for respiratory diseases in U.S. cities (Atlanta, GA, Birmingham, AL, St. Louis, MO, and Dallas, TX). Authors obtained medical data from hospital electronic billings for emergency department visits due to respiratory disease, identified using ICD-9 codes (460-465, 466, 477, 480-486, 491, 492, 493, 496, 786.07). Authors collected PM<sub>2.5</sub> concentrations from one ambient air monitor in each of the four cities and gathered meteorological data from the National Climactic Data Center. (Krall, Anderson et al. 2013) estimated source specific PM<sub>2.5</sub> using apportionment models, which separate PM<sub>2.5</sub> sources based on chemical composition. This model also included data on gaseous pollutant concentrations from the Community Multiscale Air Quality (CMAQ) with Tracers model. (Krall, Anderson et al. 2013) used Poisson time series regression models to analyze associations between short-term PM<sub>2.5</sub> exposure and emergency department visits for respiratory diseases. They then compared source specific PM<sub>2.5</sub> exposures across cities to estimate associations with the emergency department visit data. To limit confounders, the authors adjusted models for indicator variables, meteorological variables, and long-term trends in emergency department visits. The identified relative risk estimates of 1.005 (95% CI: 1.000-1.010) for Atlanta, GA; 1.009 (95% CI: 1.003-1.015) for Birmingham, AL; 1.008 (95% CI: 1.002-1.014) for St. Louis, MO; and 1.012 (95% CI: 1.002-1.023) for Dallas, TX were calculated from a single-pollutant model for a 9.16 µg/m<sup>3</sup> increase in daily mean PM<sub>2.5</sub> concentrations, lagged by 0 days.

#### 2.3.1.9 Asthma Onset

The 2019 PM ISA stated that “longitudinal studies provide evidence of associations with asthma incidence in children” and found “evidence for a relationship between PM<sub>2.5</sub> exposure and asthma prevalence in children and childhood wheeze” ((U.S. EPA 2019)). Additionally, asthma onset was called out as a key clinically relevant health endpoint in the biological plausibility pathways included in the ISA (section 2.2.1.2.1.2) ((U.S. EPA 2019)).

#### 2.3.1.9.1 Available Epidemiologic Literature

The final 2019 PM ISA found that “recent studies of asthma in children supplement the limited number of studies reviewed in the 2009 PM ISA and provide evidence of an association between long-term PM<sub>2.5</sub> exposure and asthma development in children” ((U.S. EPA 2019)). There was also evidence of PM<sub>2.5</sub>-attributable asthma onset in adults, but results were inconsistent across studies. As a result, asthma onset in adults is not included in our main benefits assessment.



Five North American epidemiologic studies of asthma onset in children were identified in section 5.2 of the 2019 PM ISA ((U.S. EPA 2019)). Relevant information related to the identification criteria, including study location, population attributes, and study period, were extracted from the studies and is available in the corresponding Excel file.

#### 2.3.1.9.2 Identifying Suitable Studies for Use in Benefits Assessments

Although the available asthma onset studies vary widely in all criteria considered, relevant study information was again used to identify the most nationally representative study or studies (see Excel file). Interestingly, three of the five studies were conducted in Canada.<sup>47</sup> One study conducted in Canada evaluated a recent and extensive time series of air quality and health data; assigned exposures to populations using a combination of monitor and remote sensing data; validated the outcome measure; observed effects with relatively low ( $\sim 10 \mu\text{g}/\text{m}^3$ )  $\text{PM}_{2.5}$  concentrations and included over 30-fold the number of participants as any other study. Other available literature was also more limited with regards to population demographic and geographic diversity.

#### 2.3.1.9.3 Study Identified as Most Suitable for Use in Benefits Assessments

(Tetreault, Doucet et al. 2016) investigated the relationship between childhood asthma onset and long-term pollution exposure ( $\text{PM}_{2.5}$ ,  $\text{NO}_2$ ,  $\text{O}_3$ ) in Quebec, Canada. The authors obtained data from four medical-administrative databases collectively known as Quebec Integrated Chronic Disease Surveillance System (QICDSS) between April 1, 1996 and March 31, 2011. The study defined the onset of asthma as a hospital discharged diagnosis of asthma or two reports of asthma from two separate physicians within a two-year period. The authors used Cox proportional hazard models to estimate the association between asthma onset and pollution exposure, controlling for demographics and socioeconomic status. Time-varying exposure models assessed time-varying exposures to the three pollutants in question. (Tetreault, Doucet et al. 2016) showed that childhood asthma onset may be associated with exposure to  $\text{PM}_{2.5}$ ,  $\text{NO}_2$ , and  $\text{O}_3$ .

The identified study presented 24 hazard ratios using various adjustment methods and included multiple sensitivity analyses, evaluating the effects by sex, urbanicity, and those who moved during the study period. More-adjusted risk estimates using a time-varying estimate of  $\text{PM}_{2.5}$  exposure and including the full cohort were identified over less-adjusted or stratified estimates using exposure estimates at birth. The study identified as best characterizing risk across the U.S. was (Tetreault, Doucet et al. 2016), although the two older and demographic-limited U.S. studies were also identified as potentially informative.

The risk estimate identified from (Tetreault, Doucet et al. 2016) for use in the main benefits estimates was a single-pollutant time-varying hazard ratio model of 1.33 (95% CI: 1.31-1.34) for a  $6.53 \mu\text{g}/\text{m}^3$  (interquartile range) increase in annual  $\text{PM}_{2.5}$  concentration at the residential address.

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<sup>47</sup> Although several key studies identified in the 2019 PM ISA come from Europe, we excluded studies outside of North America. Studies taking place in Canada were retained, as there is considerable  $\text{PM}_{2.5}$  transport between Canada and the US (<https://www.epa.gov/airmarkets/canada-united-states-transboundary-particulate-matter-science-assessment-2013>),  $\sim 90\%$  of Canadians live within  $\sim 100$  miles of the US border (<https://www.cbc.ca/news/canada/by-the-numbers-1.801937>), and ambient  $\text{PM}_{2.5}$  concentrations are similar in Canada and the US. Additionally, this endpoint is more related to health physiology than healthcare systems and Canada and the US have similar prevalence rates of asthma (<https://ourworldindata.org/grapher/asthma-prevalence>).

As the physiology and etiology of lung development in children is similar in children 6-17, we apply the 4-12 year age-stratified effect estimate from (Tetreault, Doucet et al. 2016) to children ages 4-17 ((Sparrow, O'Connor et al. 1991, Guerra, Wright et al. 2004, Ochs, Nyengaard et al. 2004, Baena-Cagnani, Rossi et al. 2007, Trivedi and Denton 2019)).

#### 2.3.1.10 Asthma Symptoms/Exacerbation

The 2019 PM ISA stated that “evidence for effects on asthma exacerbation are generally more consistent than associations for other respiratory outcomes.” The ISA went on to note that “recent studies strengthen the relationship between asthma exacerbation in children and short-term PM<sub>2.5</sub> exposure, while, in adults, the relationship continues to be inconsistent” ((U.S. EPA 2019)).

##### 2.3.1.10.1 Available Epidemiologic Literature

Based on evidence provided by the 2019 PM ISA, available studies of asthma symptoms were limited to children, of which there were eight.

##### 2.3.1.10.2 Identifying Suitable Studies for Use in Benefits Assessments

Due to the specificity required when evaluating this health endpoint, individual studies of asthma exacerbation/symptoms tended to focus on relatively small cohorts of children of discrete ages in distinct locations, making pooling difficult. One study evaluated a directly monetizable outcome of albuterol inhaler use. Albuterol inhalers are separated from long-term asthma control medications and is considered a “rescue medication” by the Mayo Clinic, making it an informative endpoint when considering asthma symptoms.<sup>48</sup>

##### 2.3.1.10.3 Studies and Risk Estimates Identified as Most Suitable for Use in Benefits Assessments

(Rabinovitch, Strand et al. 2006) analyzed the relationship between short-term PM<sub>2.5</sub> exposure and asthma exacerbation in children. The study followed children, ages 6 to 13 attending the Kunsberg School at the National Jewish Medical Research Center with diagnosed asthma for two consecutive winters from 2001-2003. Authors gave an electronic bronchodilator (albuterol) to the children to capture the frequency of use within a 24-hour period. The children also responded to three questions to determine if they may have an upper respiratory infection (URI), and urine samples were taken to measure urinary leukotriene E<sub>4</sub> levels on select days. The authors collected hourly ambient PM<sub>2.5</sub> levels from the Colorado Department of Health Air Pollution Control Division’s Tapered Element Oscillating Microbalance (TEOM) monitor, located 2.7 miles west of the school. Additionally, a Federal Reference Monitor (FRM) located next to the TEOM measured 24-hour PM<sub>2.5</sub> levels. The authors obtained meteorological data from the Colorado Department of Health Air Pollution Control Division and the National Climatic Data Center. A Poisson regression modeled albuterol use as a function of the morning (12:00am to 11:00 am) maximum hourly PM<sub>2.5</sub> level or the morning mean hourly PM<sub>2.5</sub> level. The model used both the TEOM and FRM data, individually, incorporated four lag periods (0 to 2 days and 0- to 2-day average), and included several covariates: temperature, pressure, humidity, time trend, Friday indicator, and URI indicator. (Rabinovitch, Strand et al. 2006) found that, although the PM<sub>2.5</sub> pollution levels were well below the National Ambient Air Quality Standards, there is a consistent association between peak ambient PM<sub>2.5</sub> levels and increased albuterol use in asthmatic children. The identified percent of use increase estimate of 1.2% (95% CI: -0.6-2.9) for a 6 µg/m<sup>3</sup> increase in averaged daily mean PM<sub>2.5</sub> concentration lagged by 0-, 1-, and 2-days came from a single-pollutant model. As the

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<sup>48</sup> <https://www.mayoclinic.org/diseases-conditions/asthma/in-depth/asthma-medications/art-20045557>

physiology and etiology of lung development in children is similar in children 6-17, we apply the 6-13-year age-stratified effect estimate to children ages 6 to 17 ((Sparrow, O'Connor et al. 1991, Guerra, Wright et al. 2004, Ochs, Nyengaard et al. 2004, Baena-Cagnani, Rossi et al. 2007, Trivedi and Denton 2019)).

#### **2.3.1.11 Allergic Rhinitis (Hay Fever/Respiratory Allergies)**

The 2019 PM ISA stated that “recent studies evaluated associations between long-term exposure to PM<sub>2.5</sub> and various allergic outcomes in a mix of large representative cohort and cross-sectional survey studies” finding “generally consistent evidence of an association between long-term PM<sub>2.5</sub> exposure and allergic sensitization in single pollutant models” ((U.S. EPA 2019), section 5.2.4). Additionally, the ISA called out “allergic responses” in the biological plausibility diagram for long-term PM<sub>2.5</sub>-attributable respiratory effects ((U.S. EPA 2019), section 2.2.1.2.1.2). Although cross sectional analyses do not establish a temporal sequence, they can be used to estimate benefits associated with changes in air quality.

##### **2.3.1.11.1 Available Epidemiologic Literature**

The 2019 PM ISA identified one epidemiologic study of long-term 2019 PM<sub>2.5</sub> exposure and allergic rhinitis ((U.S. EPA 2019)).

##### **2.3.1.11.2 Studies and Risk Estimates Identified as Most Suitable for Use in Benefits Assessments**

(Parker, Akinbami et al. 2009) investigated the associations between long-term PM<sub>2.5</sub> exposure and respiratory allergies in an unrestricted population of children (aged 3-17 years) sampled from the United States National Health Interview Survey. Authors obtained symptom data from participant parents, who reported respiratory allergies on annual surveys. (Parker, Akinbami et al. 2009) placed all study participants reporting symptoms of respiratory allergies or hay fever into a combined rhinitis group. (Parker, Akinbami et al. 2009) then linked annual averages of SO<sub>2</sub>, NO<sub>2</sub>, PM<sub>2.5</sub>, and PM<sub>2.5-10</sub> and warm season (May to September) O<sub>3</sub> averages to participant’s addresses through ambient air pollution and meteorological data (O<sub>3</sub>, SO<sub>2</sub>, NO<sub>2</sub>, PM<sub>2.5</sub>, and PM<sub>10-2.5</sub>) collected from US EPA Air Quality System monitors. The authors adjusted models for survey year, poverty-level, race/ethnicity, age, family structure, insurance coverage, usual source of care, education of adult, urban-rural status, region, and median county-level income. Through multi-pollutant, logistic regression models, an odds ratio of 1.29 (95% CI: 1.07-1.56) for a 10 µg/m<sup>3</sup> increase in PM<sub>2.5</sub> concentrations and respiratory allergies was identified.

#### **2.3.1.12 Minor Restricted Activity Days**

No new epidemiologic studies of minor restricted activity days (MRADs) were identified in the 2019 PM ISA ((U.S. EPA 2019)).

##### **2.3.1.12.1 Studies and Risk Estimates Identified as Most Suitable for Use in Benefits Assessments**

(Ostro and Rothschild 1989) estimated the impact of PM<sub>2.5</sub> and O<sub>3</sub> on the incidence of minor restricted activity days (MRADs) and respiratory-related restricted activity days (RRADs) in a national sample of the adult working population, ages 18 to 65, living in metropolitan areas. The study population is based on the Health Interview Survey (HIS), conducted by the National Center for Health Statistics. In publications from this ongoing survey, non-elderly adult populations are generally reported as ages 18-64. From the study, it is not clear if the age range stops at or includes those aged 65. We apply the risk estimate function to individuals ages 18-64 for consistency with other studies estimating impacts to non-elderly

adult populations. The annual national survey results used in this analysis were conducted in the period 1976-1981, controlling for PM<sub>2.5</sub>, two-week average O<sub>3</sub>.

### 2.3.1.13 *Work Loss Days*

No new studies of work loss days (WLDs) were identified in the 2019 PM ISA ((U.S. EPA 2019)).

2.3.1.13.1 Studies and Risk Estimates Identified as Most Suitable for Use in Benefits Assessments (Ostro 1987) estimated the impact of PM<sub>2.5</sub> on the incidence of work-loss days (WLDs), restricted activity days (RADs), and respiratory-related RADs (RRADs) in a national sample of the adult working population, ages 18 to 65, living in metropolitan areas. The study population is based on the Health Interview Survey (HIS), conducted by the National Center for Health Statistics. The annual national survey results used in this analysis were conducted in 1976-1981. (Ostro 1987) reported that two-week average PM<sub>2.5</sub> levels were significantly linked to work-loss days, RADs, and RRADs, however there was some year-to-year variability in the results. Separate coefficients were developed for each year in the analysis (1976-1981); these coefficients were pooled. The coefficient used in the concentration-response function presented here is a weighted average of the coefficients in (Ostro 1987), Table III, using the inverse of the variance as the weight.

### 2.3.1.14 *Lung Cancer*

The 2019 PM ISA determined that a “likely to be causal” relationship exists between long-term PM<sub>2.5</sub> exposure and cancer ((U.S. EPA 2019)), a change in the causality determination from the 2009 ISA ((U.S. EPA 2009)). Specifically, the ISA found evidence of generally consistent positive associations between long-term PM<sub>2.5</sub> exposure and lung cancer incidence.<sup>49</sup> Additional details regarding potential pathways of disease development are summarized in the biological plausibility diagram provided by the ISA (section 2.2.1.2.1.3).

For an outcome such as lung cancer, there is an expected time lag between changes in pollutant exposure in a given year and the reduction in lung cancer incidence, known as the latency period. The time between exposure and diagnosis can be quite long, on the order of years to decades. We discuss methods used to account for the latency period and other economic considerations relevant to this health endpoint in section 5.3.6. Importantly, we include this health endpoint to assess impacts of living with a lung cancer diagnosis, prior to disease resolution or death.

#### 2.3.1.14.1 Available Epidemiologic Literature

We limited our pool of available studies to those of lung cancer incidence, excluding those assessing lung cancer mortality as that endpoint is included in the long-term exposure-attributable all-cause mortality endpoint (section 2.3.1.1.3.1). This resulted in four study options.

#### 2.3.1.14.2 Identifying Suitable Studies for Use in Benefits Assessments

The four available studies varied in terms of population demographics included and country. Two of the four studies took place entirely in Canada. Of the two U.S.-based studies, one included all ages, sexes, and demographics and was restricted to non- and never-smokers, although it included some participants

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<sup>49</sup> The ISA also found generally consistent positive associations between long-term PM<sub>2.5</sub> exposure and lung cancer mortality, but as mortality impacts are included elsewhere (section 2.3.1.1), this endpoint focuses on non-fatal lung cancer incidence.

living in Canada. The identified study was most suitable as it took place in the U.S., included both males and females, and was restricted to non- and never-smokers ((Gharibvand, Shavlik et al. 2017)).

2.3.1.14.3 Studies and Risk Estimates Identified as Most Suitable for Use in Benefits Assessments (Gharibvand, Shavlik et al. 2017) evaluated whether positive associations exist between PM<sub>2.5</sub> exposure and incidence of lung cancer in non-smokers among the Adventist Health and Smog Study-2 (AHSMOG-2), a group of health-conscious individuals of which 81% are never smokers. Authors collected ambient air pollution data (PM<sub>2.5</sub> and O<sub>3</sub>) from the US EPA Air Quality system over two years (January 2000-December 2001). Three *a priori* factors were added to the models as covariates: time spent outdoors, residence length, and moving distance during follow-up. Authors modeled the association between PM<sub>2.5</sub> exposure and incidence of lung cancer using a Cox proportional hazards regression, with attained age as the time variable. The authors conducted both a single and a two-pollutant (PM<sub>2.5</sub> and O<sub>3</sub>) analyses. The study concluded that each 10 µg/m<sup>3</sup> increase in ambient PM<sub>2.5</sub> concentrations was positively associated with increased lung cancer risks within the single-pollutant and two-pollutant multivariable models with O<sub>3</sub>. The identified hazard ratio of 1.46 (95% CI: 1.13-1.89) for each 10 µg/m<sup>3</sup> increase in mean monthly ambient PM<sub>2.5</sub> concentrations came from a two-pollutant multivariable model with O<sub>3</sub> (including *a priori* covariates).

#### 2.3.1.15 Alzheimer's Disease

Evidence connecting long-term PM<sub>2.5</sub> exposure to nervous system effects led to the 2019 PM ISA concluding a “likely to be causal” relationship exists ((U.S. EPA 2019)) and various clinically relevant nervous system endpoints were called out in the biological plausibility section, including Alzheimer's disease, Parkinson's disease, autism spectrum disorder, cognitive decline, and dementia (section 2.2.1.2.1.3). Regarding biological plausibility, the ISA stated that “neuroinflammation and neurodegeneration provide biological plausibility for epidemiologic results of increased hospital admissions or emergency department visits for Alzheimer's and Parkinson's disease.”

There were over a dozen epidemiologic studies in the 2019 PM ISA evaluating cognitive-related outcomes ((U.S. EPA 2019), sections 8.2.5-8.2.7). However, due to the nature of the endpoint, many of the outcomes were defined using scales and scores from cognitive tests. As we are currently unable to transfer that type of result into a clinically relevant population level outcome, we focused on the more clearly defined outcomes of Alzheimer's disease and Parkinson's Disease. These endpoints were also specifically called out in the ISA, as “epidemiologic studies also provide evidence of cognitive impairment and Alzheimer's and Parkinson's disease in association with exposure to PM<sub>2.5</sub>” ((U.S. EPA 2019), section 8.2.6).

##### 2.3.1.15.1 Available Epidemiologic Literature

One epidemiologic study of Alzheimer's disease met our minimum required identification criteria (section 2.1.1).

2.3.1.15.2 Studies and Risk Estimates Identified as Most Suitable for Use in Benefits Assessments (Kioumourtzoglou, Schwartz et al. 2016) evaluated the potential impact of long-term PM<sub>2.5</sub> exposure on first hospital admission for dementia, Alzheimer's, or Parkinson's diseases among Medicare beneficiaries (>= 65 years old) in 50 cities in the northeastern U.S. (Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont, and Washington, D.C.). Authors retrieved medical data from the Center for Medicaid and Medicare from the

years 1999-2010. The study followed enrollees as a cohort, which included annual follow-up records identifying the first hospital admissions for dementia (ICD-9 290), Alzheimer's (ICD-9 331.0), Parkinson's (ICD-9 332), and other cardiovascular comorbidities. With respect to Alzheimer's disease, the study evaluated 9,817,806 Medicare enrollees and included 266,725 cause-specific hospital admissions indicating disease onset. Annual average PM<sub>2.5</sub> concentrations were estimated for each city using data from the U.S. EPA Air Quality System database. (Kioumourtzoglou, Schwartz et al. 2016) fit a time-varying Cox proportional hazards model for each city, using the city-wide annual PM<sub>2.5</sub> concentrations as the time-varying exposure of interest and a linear term for the calendar year. This eliminated the impact of PM<sub>2.5</sub> variation by city and any PM<sub>2.5</sub> trends within cities. The model adjusted for cardiovascular comorbidities, and incorporated a counting process extension which created an observation for each year of follow-up per person. The results were then pooled across individuals and cities. A single-pollutant model was used to develop the identified hazard ratio of 1.15 (95% CI: 1.11-1.19) for a 1 µg/m<sup>3</sup> increase in the average annual PM<sub>2.5</sub> concentrations.

#### *2.3.1.16 Parkinson's Disease*

Evidence connecting long-term PM<sub>2.5</sub> exposure to nervous system effects led to the 2019 ISA concluding a "likely to be causal" relation exists ((U.S. EPA 2019)) and various clinically relevant nervous system endpoints were called out in the biological plausibility section, including Alzheimer's disease, Parkinson's disease, autism spectral disorder, cognitive decline, and dementia (section 2.2.1.2.1.3). Regarding biological plausibility, the ISA stated that "neuroinflammation and neurodegeneration provide biological plausibility for epidemiologic results of increased hospital admissions or emergency department visits for Alzheimer's and Parkinson's disease."

There were over a dozen epidemiologic studies in the 2019 PM ISA evaluating cognitive-related outcomes ((U.S. EPA 2019), sections 8.2.5-8.2.7). However, due to the nature of the endpoint, many of the outcomes were defined using scales and scores from cognitive tests. As we are currently unable to transfer that type of result into a clinically relevant disease incidence, we focused on the more clearly defined outcomes of Alzheimer's disease and Parkinson's Disease. These endpoints were also specifically called out in the ISA, as "epidemiologic studies also provide evidence of cognitive impairment and Alzheimer's and Parkinson's disease in association with exposure to PM<sub>2.5</sub>" ((U.S. EPA 2019), section 8.2.6).

##### *2.3.1.16.1 Available Epidemiologic Literature*

Three epidemiologic studies of Parkinson's disease were identified in the 2019 PM ISA. All evaluated relatively low PM<sub>2.5</sub> concentrations and included participants from multiple states, however there were differences with respect to the ages and sexes evaluated, number of overall participants, and exposure estimation technique.

##### *2.3.1.16.2 Identifying Suitable Studies for Use in Benefits Assessments*

The prospective study with the lowest mean PM<sub>2.5</sub> concentrations and most recent timespan included over 14 times the number of participants as the other two studies combined. It was also the only study to include participants over the age of 71, which is relevant as Parkinson's disease prevalence rises with age ((Pringsheim, Jette et al. 2014)).

2.3.1.16.3 Studies and Risk Estimates Identified as Most Suitable for Use in Benefits Assessments (Kioumourtzoglou, Schwartz et al. 2016) evaluated the potential impact of long-term PM<sub>2.5</sub> exposure on first hospital admission for dementia, Alzheimer’s, or Parkinson’s diseases among Medicare beneficiaries (>= 65 years old) in 50 cities in the northeastern U.S. (Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont, and Washington, D.C.). Authors retrieved medical data from the Center for Medicaid and Medicare from the years 1999-2010. The study followed enrollees as a cohort, which included annual follow-up records identifying the first hospital admissions for dementia (ICD-9 290), Alzheimer’s (ICD-9 331.0), Parkinson’s (ICD-9 332), and other cardiovascular comorbidities. With respect to Parkinson’s disease, the study evaluated 9,817,806 Medicare enrollees and included 119,425 cause-specific hospital admissions indicating disease onset. Annual average PM<sub>2.5</sub> concentrations were estimated for each city using data from the US EPA Air Quality System database. (Kioumourtzoglou, Schwartz et al. 2016) fit a time-varying Cox proportional hazards model for each city, using the city-wide annual PM<sub>2.5</sub> concentrations as the time-varying exposure of interest and a linear term for the calendar year. This eliminated the impact of PM<sub>2.5</sub> variation by city and any PM<sub>2.5</sub> trends within cities. The model adjusted for cardiovascular comorbidities, and incorporated a counting process extension which created an observation for each year of follow-up per person. The results were then pooled across individuals and cities. A single-pollutant model was used to develop the identified hazard ratio of 1.08 (1.04 – 1.12) for a 1 µg/m<sup>3</sup> increase in the average annual PM<sub>2.5</sub> concentrations.

### 2.3.2 O<sub>3</sub>

The following sections of the 2020 O<sub>3</sub> ISA correspond to health endpoints judged as having a “causal” or “likely causal” relationship with O<sub>3</sub> exposure:

- Appendix 3: Health Effects – Respiratory, 3.1 Short-Term Ozone Exposure;
- Appendix 3: Health Effects – Respiratory, 3.2 Long-Term Ozone Exposure;
- Appendix 5: Health Effects – Metabolic Effects, 5.1 Short-Term Ozone Exposure;
- Appendix 6: Health Effects – Mortality, 6.1 Short-Term Ozone Exposure and Mortality; and
- Appendix 6: Health Effects – Mortality, 6.2 Long-Term Ozone Exposure and Mortality.

Following the approach to identifying available epidemiologic literature (section 2.2), we began with the 1,678 studies cited by the 2020 O<sub>3</sub> ISA ((U.S. EPA 2020)). Of these, 130 morbidity studies evaluate health endpoints the 2020 O<sub>3</sub> ISA determined as having a “causal” or “likely causal” relationship with O<sub>3</sub> exposure (sections 2.2.1 and 2.2.2). 77 studies remained after the required minimum criteria were applied, and that number decreased to 27 when broad hospital admissions and emergency department endpoints were identified.<sup>50</sup> No studies of short-term O<sub>3</sub> exposure metabolic effects meeting the minimum required criteria (section 2.1.1) were identified in the ISA.

Table 7. O<sub>3</sub> Study and Risk Estimate Identification Diagram

O <sub>3</sub> Endpoint and Exposure Duration	Studies Available	Studies Included	Ages	Risk Estimates Available	Risk Estimates Included
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<sup>50</sup> This number may not be equal to the sum of available studies in Table 7 as individual studies may present risk estimates for multiple health endpoints.

Respiratory Mortality (LT)	4	1	Adults and older adults	2	1
Respiratory Mortality (ST)	6	2	Children, adults, and older adults	16	1
				120	1
Respiratory Hospital Admissions (ST)	3	1	Older adults	7	1
Respiratory Emergency Department Visits (ST)	7	1	Children, adults, and older adults	45	5
Asthma Onset (LT)	4	1	Children	8	1
Asthma Symptoms (ST)	4	1	Children	160	1
Minor Restricted Activity Days	NA	1	Adults	NA	1
Allergic Rhinitis	1	1	Children	5	1
School Loss Days	NA	2	Children	NA	1
				NA	1

NA- not applicable due to the absence of additional ISA evidence. Risk estimates identified in the 2015 Ozone NAAQS RIA will continue to be utilized.

### 2.3.2.1 Respiratory Mortality

We separate respiratory mortality impacts resulting from short- and long-term exposures for several reasons. Firstly, the biological pathways of short- and long-term O<sub>3</sub>-attributable health effects may differ in ways that affect the manner in which this endpoint is quantified (section 2.2.1.2.2.1). For example, some impacts of long-term exposure to O<sub>3</sub> may be incremental to impacts attributable to short-term exposure. Conversely, some impacts associated with long-term exposure to O<sub>3</sub> may include impacts attributable to short-term exposure. However, we lack the evidence to determine the extent to which these risks are mutually exclusive or overlapping. Secondly, the level of support for respiratory mortality effects of short- and long-term O<sub>3</sub> exposures may differ. Therefore, we continue to include risk estimates of respiratory mortality from both short- and long-term exposures to present a range of health impact estimates.

#### 2.3.2.1.1 Respiratory Mortality Attributable to Short-Term Exposures

The 2020 O<sub>3</sub> ISA determined that there exists a “causal” relationship between short-term O<sub>3</sub> exposure and respiratory outcomes ((U.S. EPA 2020)). The short-term exposure causality determination “was made on the basis of a strong body of evidence integrated across controlled human exposure, animal toxicological, and epidemiologic studies, in addition to established findings from previous [Air Quality Criteria Documents], demonstrating respiratory effects due to short-term exposure to ozone.” While the ISA found that “recent epidemiological evidence for respiratory mortality is limited, but there remains evidence of consistent, positive associations, specifically in the summer months” and “when recent evidence is considered in the context of the larger number of studies evaluated in the 2013 Ozone ISA, there remains consistent evidence of an association between short-term ozone exposure and respiratory mortality.” Due to the strength of the ISA evidence relating short-term exposures to respiratory mortality, estimates of respiratory mortality impacts are included in the main benefits assessment of O<sub>3</sub>-attributable health impacts.

Separately, 2020 ISA determined that the relationship between short-term O<sub>3</sub> exposure and total mortality is “suggestive of, but not sufficient to infer, a causal relationship” ((U.S. EPA 2020)). By



comparison, the 2013 ISA identified this endpoint as “likely to be causal” ((U.S. EPA 2013)). Evidence supporting a relationship between short-term O<sub>3</sub> exposure and total mortality included consistent epidemiologic evidence from multiple high-quality studies at relevant ozone concentrations, some support for an independent O<sub>3</sub> association, and biological plausibility from studies of respiratory morbidity. In contrast, uncertainties remain regarding geographic heterogeneity in O<sub>3</sub> mortality associations and there is limited biological plausibility from studies of cardiovascular morbidity. Regarding the biological plausibility of cardiovascular effects, while animal toxicological studies provide evidence of cardiovascular effects, recent controlled human exposure studies do not provide evidence to support potential biological pathways. Additionally, there is a lack of coherence with epidemiologic studies of cardiovascular morbidity, specifically, cardiovascular-related emergency department visits and hospital admissions, to support cardiovascular mortality. Due to limitations in ISA evidence relating short-term exposures to total mortality, estimates of all-cause mortality impacts will not be calculated when estimating benefits attributable to changes in O<sub>3</sub> exposure.

#### *2.3.2.1.1.1 Available Epidemiologic Literature*

There were six North American studies of short-term O<sub>3</sub>-attributable respiratory mortality identified in the 2020 O<sub>3</sub> ISA, one of which was new to this review but took place entirely in ((U.S. EPA 2020)). Of the U.S.-based studies, two were single-city. The other three studies were fairly equally geographically and demographically representative, although one was a meta-analysis.

#### *2.3.2.1.1.2 Identifying Suitable Studies for Use in Benefits Assessments*

Of the six studies of short-term O<sub>3</sub>-attributable respiratory mortality, all but one study period ended during or before the year 2000 and the individual study that extended into the 2000s was geographically limited to a single city. This list also included a meta-analysis and a study that took place entirely in Canada. Two U.S.-based, nationally representative studies were identified as best characterizing risk across the U.S. for this endpoint.

#### *2.3.2.1.1.3 Studies and Risk Estimates Identified as Most Suitable for Use in Benefits Assessments*

As (Zanobetti and Schwartz 2008) investigated the effects of short-term O<sub>3</sub> exposure on mortality (all-cause, cardiovascular, stroke, and respiratory) in an unrestricted population of children, adults, and older adults (aged 0-99 years), it remained a superior analysis of short-term O<sub>3</sub>-attributable respiratory mortality. Between 1998 and 2000, the authors collected mortality data from the National Center for Health Statistic in 48 cities across the United States. Along with eight-hour ozone concentrations and meteorological data obtained from US EPA’s Air Quality System Technology Transfer Network, the authors utilized a generalized linear model with quasi-Poisson link functions to estimate the effects of short-term ozone on respiratory mortality. The model adjusted for season, day of the week, and temperature. Since ozone concentrations vary between seasons, the authors decided to restrict their analysis to ozone warm season (June - August). The identified single-pollutant, warm season excess risk estimate of 0.83% (95% CI: 0.38-1.28%) for an increase of 10 ppb in DA8 O<sub>3</sub> concentrations over a summed lag structure of zero to three days.

(Katsouyanni, Samet et al. 2009) also used time series methods to examine the relationship between short-term O<sub>3</sub> exposures and mortality across the U.S for all ages. The study utilized mortality data from the National Center for Health Statistics ([www.cdc.gov/nchs](http://www.cdc.gov/nchs)) for years 1987 through 1996, excluding accidental deaths (i.e., International Classification of Diseases (ICD]-9 800). 90 U.S. cities with population sizes varying from about 250,000 to above 9 million with the largest populations were included. Daily

number of deaths ranged from 5 to 198. All 90 cities had daily summer O<sub>3</sub> measurements. Investigators conducted extensive simulation studies to test 1) the choice of the smoothing method and basic functions used to estimate the smooth function of time in the city-specific models, and 2) the number of degrees of freedom to be used in the smooth function of time. The investigators also evaluated whether each city should be assigned the same model specification or whether each city-specific model should depend on city-specific characteristics. For the former, the same degrees of freedom (ranging from 1 to 20 df/year of data) were assigned to the smooth function of time for every city. The range was determined by choosing the minimum possible degrees of freedom per year up to a maximum degrees of freedom per year that essentially removed all variation in the data beyond time scales of one week. Also, the collective experience of the investigators indicated that using more than 20 df/year does not substantially affect the risk estimates. For the latter approach, the degrees of freedom for the smooth function of time were chosen separately for each city using a fit criterion, such as the Akaike Information Criterion (AIC), or by minimizing the partial autocorrelation function (PACF) of the residuals. Nonparametric methods underestimated the standard error of the air pollution regression coefficient, penalized splines gave relatively small bias, and PACF in combination with penalized splines performed relatively well in terms of bias. Therefore, the identified risk estimate was a summer-only penalized spline estimate of respiratory mortality of 0.73 (-0.39, 1.85) per 10 µg/m<sup>3</sup> increase in O<sub>3</sub> from distributed lag days was identified.

The two risk estimates identified are not directly comparable to previous estimates of short-term exposure-related mortality as previous estimates were of nonaccidental mortality and current estimates are of respiratory mortality.

#### 2.3.2.1.2 Respiratory Mortality Attributable to Long-Term Exposures

The 2020 O<sub>3</sub> ISA determined that there exists a “likely to be causal” relationship between long-term O<sub>3</sub> exposure and respiratory outcomes ((U.S. EPA 2020)). The overall “likely to be causal” determination for long-term exposures “was based on epidemiologic evidence of associations between long-term ozone exposure and asthma development, respiratory symptoms in children with asthma, and respiratory mortality.” More specifically, the ISA found that “there is strong coherence between animal toxicological studies of changes in lung morphology and epidemiologic studies reporting positive associations between long-term ozone exposure and new onset asthma, respiratory symptoms in children with asthma, and respiratory mortality” and the “several multicity studies and a multi-continent study reported associations between short-term increases in ozone concentrations and increases in respiratory mortality.” Overall, the 2020 O<sub>3</sub> ISA concluded there was “some evidence that long-term ozone exposure is associated with respiratory mortality, but the evidence is not consistent across studies.” Due to the strength of the ISA evidence relating long-term exposures to respiratory mortality, estimates of respiratory mortality impacts are included when estimating benefits attributable to changes in O<sub>3</sub> exposure.

##### 2.3.2.1.2.1 Available Epidemiologic Literature

There were four North American studies of long-term O<sub>3</sub>-attributable respiratory mortality identified in the 2020 O<sub>3</sub> ISA, three of which were new to this review ((U.S. EPA 2020)).<sup>51</sup> All four studies evaluated

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<sup>51</sup>The 2020 O<sub>3</sub> ISA identified five North American studies of long-term O<sub>3</sub>-attributable respiratory mortality, but as Weichenthal, S., D. L. Crouse, L. Pinault, K. Godri-Pollitt, E. Lavigne, G. Evans, A. van Donkelaar, R. V. Martin and R.

either the ACS CSP-II or the Canadian Census Health and Environment Cohort (CanCHEC) prospective cohorts, differing in study size, timespan, exposure estimation technique, and specific risk models analyzed.

#### 2.3.2.1.2.2 *Identifying Suitable Studies for Use in Benefits Assessments*

Three of the four studies evaluating long-term O<sub>3</sub>-attributable respiratory mortality assessed the ACS CSP-II prospective cohort and the fourth evaluated the Canadian Census Health and Environment Cohort (CanCHEC) prospective cohort. Two of the three ACS CSP-II analyses were nationwide, with the third focusing on California. One of the two nationwide ACS CSP-II analyses included a longer and more recent study period, utilized hybrid exposure estimates, and included a larger number of participants.

#### 2.3.2.1.2.3 *Studies and Risk Estimates Identified as Most Suitable for Use in Benefits Assessments*

(Turner, Jerrett et al. 2016) examined the relationship between long-term O<sub>3</sub> exposure (1982-2004) and mortality (all-cause, cause-specific) in American Cancer Society Cancer Prevention Study-II participants (aged 30-99 years). A hierarchical Bayesian space-time model based on National Air Monitoring Stations, State and Local Air Monitoring Stations, and Community Multi-Scale Air Quality model data estimated daily eight-hour maximum ozone concentrations at the participant's address. The models considered meteorological data and levels of other ambient pollutants (PM<sub>2.5</sub>, both regional and near-source, and NO<sub>2</sub>). (Turner, Jerrett et al. 2016) utilized Cox proportional hazard models adjusted *a priori* for individual, socio-demographic, and ecological variables. The hazard ratio of 1.12 (1.08 – 1.16) from a multi-pollutant, all-year model of respiratory mortality for a 10-ppb increase in the annual average of daily 8-hour maximum ozone concentrations was likely the most comprehensive risk estimate. This study also provided a warm-season specific hazard ratio of 1.08 (1.06-1.11) per 10 ppb increase in seasonal average of daily 8-hour maximum O<sub>3</sub> concentrations, which will be used when air quality surfaces are only available for the summer season. Notably, the study compared annual mortality with warm-season O<sub>3</sub> exposures, so full-year baseline incidence rates will be used with risk estimates from this study.

The identified risk estimate of long-term exposure associated mortality is larger than the risk estimate used in previous benefits assessments ((Jerrett, Burnett et al. 2009)), but differs in many aspects including study size, included study locations, and exposure estimation technique.

#### 2.3.2.2 *Respiratory Hospital Admissions*

After considering the relationships between specific and broad respiratory hospital admission endpoints, the 2020 O<sub>3</sub> ISA stated that “studies conducted in diverse locations with a variety of exposure assignment techniques continue to provide evidence of an association between ozone and both hospital admissions and emergency department visits for combined respiratory diseases” ((U.S. EPA 2020), section 3.1.8).

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T. Burnett (2016). "Oxidative burden of fine particulate air pollution and risk of cause-specific mortality in the Canadian Census Health and Environment Cohort (CanCHEC)." *Environmental Research* **146**: 92-99. examined the combined oxidant capacity of O<sub>3</sub> and NO<sub>2</sub>, and not direct effects of O<sub>3</sub> alone, it did not meet required minimum criteria for consideration for inclusion in benefits assessments (section 2.1.1).

#### 2.3.2.2.1 Available Epidemiologic Literature

Three epidemiologic studies of respiratory hospital admission were identified in the 2020 O<sub>3</sub> ISA, which varied considerably with respect to the timespans evaluated and study population locations ((U.S. EPA 2020)).

#### 2.3.2.2.2 Identifying Suitable Studies for Use in Benefits Assessments

The two older studies either included only Canadian participants or included U.S., Canadian, and some European participants. Therefore, we identified the most recent and only entirely U.S.-based study as best characterizing risk across the U.S.

#### 2.3.2.2.3 Studies and Risk Estimates Identified as Most Suitable for Use in Benefits Assessments

(Katsouyanni, Samet et al. 2009) used time series methods to examine the relationship between daily O<sub>3</sub> concentrations and hospital admissions in North America. For U.S. benefits estimation purposes, we focus on analyses performed using the U.S hospital admission datasets. These datasets included 14 cities with populations between 291,000 and 5,377,000 between 1987-1996 with city-wide MDA1 O<sub>3</sub> concentrations ranging from ~34-60 µg/m<sup>3</sup>. The authors used a first stage analysis protocol that used generalized linear models with either penalized or natural splines to adjust for seasonality, with varying degrees of freedom. The number of degrees of freedom were also chosen by minimizing the partial autocorrelation function of the model's residuals. Model specification approach accounted for seasonal patterns, weekend and vacation effects, and epistemics of respiratory disease. Data were also analyzed to detect potential thresholds in the concentration-response relationships. The second stage analysis used pooling approaches and assessed potential effect modification by sociodemographic characteristic and indicators of the pollution mixture across study regions. The identified percent change in respiratory disease admission for those aged >64 was from a copollutant model including PM<sub>10</sub> is 0.28 (-0.07, 0.62) per 10 µg/m<sup>3</sup> increase in O<sub>3</sub>.

#### 2.3.2.3 Respiratory Emergency Department Visits

After considering the relationships between specific and broad respiratory emergency department visit endpoints, the 2020 O<sub>3</sub> ISA stated that “studies conducted in diverse locations with a variety of exposure assignment techniques continue to provide evidence of an association between ozone and both hospital admissions and emergency department visits for combined respiratory diseases” and “there is some evidence, previously characterized in the 2013 O<sub>3</sub> ISA, that daily 8 hour max, 1 hour max, and daytime average O<sub>3</sub> concentrations may be most strongly associated with respiratory emergency department visits” ((U.S. EPA 2020), section 3.1.8).

#### 2.3.2.3.1 Available Epidemiologic Literature

Seven U.S.-based studies of respiratory emergency department visits were identified in the 2020 O<sub>3</sub> ISA ((U.S. EPA 2020)). As is common with hospital admission and emergency department health endpoints, the specific ICD codes varied across all studies, making pooling difficult. Most studies evaluated only a single city or state and took place in a similar time period, including the early 2000s.

#### 2.3.2.3.2 Identifying Suitable Studies for Use in Benefits Assessments

Available studies varied most widely by geographic area, exposure estimation method, population age range, and O<sub>3</sub> season. While most studies focused on a specific city, state or region, one study included five different multi-county areas. In addition, it included a recent time period, all ages, current O<sub>3</sub> concentrations, and was one of only two studies based on hybrid exposure techniques.

2.3.2.3.3 Studies and Risk Estimates Identified as Most Suitable for Use in Benefits Assessments (Barry, Klein et al. 2019) investigated the effects of short-term ozone exposure on emergency department visits for respiratory disease (ICD-9 493, 786.07, 460-466, 477, 491, 492, 496, 480–486, 466.1, 466.11, 466.19) in an unrestricted population of children, adults, and older adults (aged zero-99 years) within five cities (Atlanta, GA, Birmingham, AL, Dallas, TX, Pittsburgh, PA, and St. Louis, MO-IL) across the United States. Authors obtained individual-level health data from hospitals and hospital associations in each of the five cities. Models fusing air quality monitor data with Community Multi-Scale Air Quality modeled data at 12 x 12-km grids were used to estimate ozone exposure. (Barry, Klein et al. 2019) assessed associations with short-term ozone exposure with daily eight-hour maximum ozone concentrations. The authors implemented Poisson log-linear models to estimate risk values with three day moving averages. They identified single-pollutant rate ratios of 1.03 (95% CI: 1.01-1.05) in Atlanta, GA, 1.03 (95% CI: 1.00-1.06) in Birmingham, AL, 1.05 (95% CI: 1.02-1.07) in Dallas TX, 1.03 (95% CI: 1.01-1.05) in Pittsburgh, PA, and 1.02 (95% CI: 1.01-1.04) in St. Louis, MO-IL for an increase of 25 ppb in full-year MDA8 O<sub>3</sub> concentrations (three day moving average). Results from individual cities are pooled.

#### 2.3.2.4 *Asthma Onset*

The 2020 O<sub>3</sub> ISA concluded that “recent epidemiologic studies provide generally consistent evidence for associations of long-term ozone exposure with the development of asthma in children” ((U.S. EPA 2020), section IS.4.3). The ISA also found that “recent animal toxicological studies demonstrate effects on airway development in rodents...and build on and expand the evidence for long-term ozone exposure-induced effects that may lead to asthma development” and asthma onset was called out as a key population level clinically relevant health endpoint in the biological plausibility pathways (section 2.2.1.2.2.1, Figure 9). More specifically, the O<sub>3</sub> ISA stated that a “limited number of recent epidemiologic studies provide generally consistent evidence that long-term ozone exposure is associated with the development of asthma in children” ((U.S. EPA 2020), section 3.2.6).

##### 2.3.2.4.1 Available Epidemiologic Literature

The 2020 O<sub>3</sub> ISA identified children as the population in which this health effect was observed, so we began with the four ISA-identified studies of people <21 ((U.S. EPA 2020)).

##### 2.3.2.4.2 Identifying Suitable Studies for Use in Benefits Assessments

Three studies evaluated prospective cohorts, two of which included more recent timespans and likely lower O<sub>3</sub> concentrations. One of those studies took place entirely in Canada but included a substantially larger study size (>200 times larger) than the other. As the asthma onset endpoint is consistent between studies, pooling may be appropriate.

2.3.2.4.3 Studies and Risk Estimates Identified as Most Suitable for Use in Benefits Assessments (Tetreault, Doucet et al. 2016) investigated the effects of long-term O<sub>3</sub> exposure on asthma onset in children (aged zero-12 years) from Québec, Canada. The study followed participants from the Québec Integrated Chronic Disease Surveillance System open birth cohort between 1999 and 2011. The authors defined new cases of asthma based on hospital discharge reports and physician diagnoses (two diagnoses within a two-year span). Monitor data (Canadian National Air Pollution Surveillance network) and land-use mixed effect models estimated warm season (June to August) O<sub>3</sub> exposures. Authors assessed associations with asthma onset with both time of birth and time-varying exposure models and adjusted for year of birth, sex, and indices of social and material deprivation. (Tetreault, Doucet et al. 2016) used Cox proportional hazard models to observe associations between long-term O<sub>3</sub> exposure and

asthma onset in children. The identified single-pollutant, warm-season hazard ratio was 1.07 (95% CI: 1.06-1.08) for a 3.26 ppb (interquartile range) increase in annual O<sub>3</sub> concentrations.

As the physiology and etiology of lung development in children is similar in children 6-17 ((Sparrow, O'Connor et al. 1991, Guerra, Wright et al. 2004, Ochs, Nyengaard et al. 2004, Baena-Cagnani, Rossi et al. 2007, Trivedi and Denton 2019)), we apply the 4-12 year age-stratified effect estimate from (Tetreault, Doucet et al. 2016) to children ages 4-17.

### 2.3.2.5 *Asthma Symptoms*

Asthma symptoms/exacerbation is identified as a health effect of short-term O<sub>3</sub> exposure (section 2.2.1.2.2.1). Overall, the ISA found that “evidence from recent epidemiologic and experimental studies continues to support an association between ozone and asthma exacerbation” with “associations...observed across a range of ozone concentrations, and...consistent in models with measured or modeled concentrations” ((U.S. EPA 2020), section 3.1.5.7).

#### 2.3.2.5.1 Available Epidemiologic Literature

Four epidemiologic studies of asthma symptoms meeting our minimum criteria (section 2.1.1) were identified in the 2020 O<sub>3</sub> ISA ((U.S. EPA 2020)). Most studies took place in the late nineties and very early 2000s, and although no study included >1000 participants, there was appreciable geographic representation. There were also differences regarding the ozone season. Only the oldest study specifically evaluated a warm season, although a more recent study did skew slightly toward warmer seasons, evaluating eight seasons over a four-year timespan (two Summers, three Springs, two Falls, and one Winter).

#### 2.3.2.5.2 Identifying Suitable Studies for Use in Benefits Assessments

Two of the studies evaluated much higher O<sub>3</sub> concentrations (~50 ppb vs 30 ppb). Of the two studies evaluating lower pollutant concentrations, one employed a prospective study design and clearly defined the specific asthma symptoms evaluated (e.g., wheeze).

#### 2.3.2.5.3 Studies and Risk Estimates Identified as Most Suitable for Use in Benefits Assessments

(Lewis, Robins et al. 2013) studied the effects of short-term O<sub>3</sub> exposure on frequency of asthma symptoms in an asthmatic population of primarily lower-income, African American and Latino children (aged five-12 years) in East and Southwest Detroit, MI. Authors obtained health and demographic data through questionnaires filled out by parents or guardians for 14 consecutive days in each studied season. Questionnaires highlighted participant's asthma symptoms (cough, wheeze, shortness of breath, chest tightness), demographic information, medication use, and presence of second-hand smoke. The authors acquired maximum one-hour and maximum 8-hour O<sub>3</sub> concentrations and meteorological data from two community-level monitors placed on East and Southwest Detroit, MI school rooftops. (Lewis, Robins et al. 2013) implemented a combination of generalized estimating equations and alternative logistic regression models to estimate the associations between short-term O<sub>3</sub> exposure and rate of asthma symptoms. Models adjusted for age, sex, location (Eastside or Southwest), race, household income, smoker in the home, season, and variables for companion home intervention study (control or intervention), time (pre- or post-intervention), and the interaction between intervention group status and time. (Lewis, Robins et al. 2013) observed positive associations between short-term O<sub>3</sub> exposure and asthma symptoms, including the identified single-pollutant, all year odds ratios of 1.12 (95% CI: 0.99-1.25) for cough, 1.13 (95% CI: 0.99-1.28) for wheeze, 1.20 (95% CI: 1.02-1.40) for chest tightness,

and 1.07 (95% CI: 0.95-1.21) for shortness of breath, all for a 16 ppb (interquartile range) increase in 8-hour maximum O<sub>3</sub> concentrations (five-day average lag).<sup>52</sup>

### **2.3.2.6 Minor Restricted Activity Days**

No new epidemiologic studies of minor restricted activity days (MRADs) were identified in the 2020 O<sub>3</sub> ISA ((U.S. EPA 2020)).

2.3.2.6.1 Studies and Risk Estimates Identified as Most Suitable for Use in Benefits Assessments (Ostro and Rothschild 1989) estimated the impact of PM<sub>2.5</sub> and O<sub>3</sub> on the incidence of minor restricted activity days (MRADs) and respiratory-related restricted activity days (RRADs) in a national sample of the adult working population, ages 18 to 65, living in metropolitan areas. The study population is based on the Health Interview Survey (HIS), conducted by the National Center for Health Statistics. In publications from this ongoing survey, non-elderly adult populations are generally reported as ages 18-64. From the study, it is not clear if the age range stops at or includes those aged 65. We apply the risk estimate function to individuals ages 18-64 for consistency with other studies estimating impacts to non-elderly adult populations. The annual national survey results used in this analysis were conducted in the period 1976-1981, controlling for PM<sub>2.5</sub>, two-week average O<sub>3</sub>.

### **2.3.2.7 Allergic Rhinitis (Hay Fever/Respiratory Allergies)**

The 2020 O<sub>3</sub> ISA stated that “cross-sectional epidemiologic studies provide generally consistent evidence that ozone concentrations are associated with hay fever/rhinitis” and included “allergic responses” in the biological plausibility diagram for long-term O<sub>3</sub>-attributable respiratory effects ((U.S. EPA 2020), section 2.2.1.2.2.1). Although cross sectional analyses do not establish a temporal sequence, they can be used to estimate benefits associated with changes in air quality.

#### **2.3.2.7.1 Available Epidemiologic Literature**

The 2020 O<sub>3</sub> ISA identified one epidemiologic study of long-term O<sub>3</sub> exposure and allergic rhinitis.

2.3.2.7.2 Studies and Risk Estimates Identified as Most Suitable for Use in Benefits Assessments (Parker, Akinbami et al. 2009) investigated the associations between long-term O<sub>3</sub> exposure and respiratory allergies in an unrestricted population of children (aged 3-17 years) sampled from the United States National Health Interview Survey. Authors obtained symptom data from participant parents, who reported respiratory allergies on annual surveys. (Parker, Akinbami et al. 2009) placed all study participants reporting symptoms of respiratory allergies or hay fever into a combined rhinitis group. (Parker, Akinbami et al. 2009) linked annual averages of SO<sub>2</sub>, NO<sub>2</sub>, PM<sub>2.5</sub>, and PM<sub>2.5-10</sub> and warm season (May to September) O<sub>3</sub> averages to participant’s addresses through ambient air pollution and meteorological data collected from US EPA Air Quality System monitors. The authors adjusted models for survey year, poverty-level, race/ethnicity, age, family structure, insurance coverage, usual source of care, education of adult, urban-rural status, region, and median county-level income. Through multi-pollutant, logistic regression models, the odds ratio of 1.18 (95% CI: 1.09-1.27) for a 10-ppb increase in 24-hour mean, warm season O<sub>3</sub> and respiratory allergies was identified.

### **2.3.2.8 School Loss Days**

No new studies of work loss days (WLDs) were identified in the 2020 O<sub>3</sub> ISA ((U.S. EPA 2020)).

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<sup>52</sup> Estimates were obtained from figures. Authors did not respond to requests for exact results.

2.3.2.8.1 Studies and Risk Estimates Identified as Most Suitable for Use in Benefits Assessments (Gilliland, Berhane et al. 2001) examined the association between air pollution and school absenteeism among fourth grade school children (aged nine to 10) in 12 southern Californian communities. The study was conducted from January through June 1996. The authors used school records to collect daily absence data and parental telephone interviews to identify causes. They defined illness-related absences as respiratory or non-respiratory. A respiratory illness was defined as an illness that included at least one of the following: runny nose/sneezing, sore throat, cough, earache, wheezing, or asthma attack. The authors used 15- and 30-day distributed lag models to quantify the association between O<sub>3</sub> and incident school absences. O<sub>3</sub> levels were positively associated with all school absence measures and significantly associated with all illness-related school absences (non-respiratory illness, respiratory illness, URI and LRI). The health impact function for ozone is based on the results of the single pollutant model.

(Gilliland, Berhane et al. 2001) defines an incident absence as an absence that followed attendance on the previous day and the incidence rate as the number of incident absences on a given day over the population at risk for an absence on a given day (i.e., those children who were not absent on the previous day). Since school absences due to air pollution may last longer than one day, an estimate of the average duration of school absences could be used to calculate the total avoided school loss days from an estimate of avoided new absences. A simple ratio of the total absence rate divided by the new absence rate would provide an estimate of the average duration of school absences, which could be applied to the estimate of avoided new absences as follows:

$$Duration = \frac{TotalAbsences}{NewAbsences}$$

$$\Delta TotalAbsences = -[incidences \times (e^{-\beta \times O_3} - 1)] \times duration \times pop$$

Since the function is log-linear, the baseline incidence rate (in this case, the rate of new absences) is multiplied by duration, which reduces to the total school absence rate. Therefore, the same result would be obtained by using a single estimate of the total school absence rate in the risk estimate. Using this approach, we assume that the same relationship observed between pollutant and new school absences in the study would be observed for total absences on a given day. As a result, the total school absence rate is used in the function below. The derivation of this rate is described in the section on baseline incidence rate estimation.

For all absences, the coefficient and standard error are based on a percent increase of 16.3 percent (95% CI -2.6 percent, 38.9 percent) associated with a 20-ppb increase in eight-hour average ozone concentration (2001, Table 6, p. 52).

A scaling factor is used to adjust for the number of school days in the ozone season. In the modeling program, the function is applied to every day in the ozone season (May 1 - September 30), however, in reality, school absences will be avoided only on school days. We assume that children are in school



during weekdays for all of May, two weeks in June, one week in August, and all of September. This corresponds to approximately 2.75 months out of the five-month season, resulting in an estimate of 39.3% of days ( $2.75/5*5/7$ ).

In addition, not all children are at-risk for a new school absence, as defined by the study. On average, 5.5% of school children are absent from school on a given day ((NCES 1996), Table 42-1). Only those who are in school on the previous day are at risk for a new absence ( $1-0.055 = 94.5\%$ ). As a result, a factor of 94.5% is used in the function to estimate the population of school children at-risk for a new absence.

## **2.4 IDENTIFIED STUDY AND RISK ESTIMATES FOR BENEFITS ASSESSMENTS**

While we begin with studies identified in ISAs, the goals of an ISA differ greatly from those of benefits assessments. ISAs evaluate the overall state of the science and develop overarching conclusions relating exposure to health effects. This includes analyses of specific subgroups, such as people with pre-existing conditions, that may not be transferrable to the entire U.S. population.

In an effort to make our study and risk estimate identification process as transparent and reproducible as possible, we have explicitly stated the criteria used in our approach (section 0) as well as the available epidemiologic studies evaluated (section 2.2). However, even with such detailed information, expert judgment can be required if multiple estimates meet the required criteria, satisfy a similar number of preferred criteria, and are unable to be statistically aggregated into a single risk estimate (i.e., pooling).

The two tables in this section provide information on the health endpoints and risk estimates identified for use in  $PM_{2.5}$  and  $O_3$  benefits estimation (Table 10 and Table 11) using the systematic approach described above (sections 2.1 and 2.2).

### 2.4.1 Health Endpoints

These summary tables provided an overview of the PM<sub>2.5</sub> and O<sub>3</sub> health endpoints included in the main benefits analysis. They are the outcome of the systematic approach described above, which involved consideration of recent ISA conclusions along with the availability of clinically relevant epidemiologic risk estimates (Table 8 and Table 9).

#### 2.4.1.1 PM<sub>2.5</sub>

Table 8. Set of Health Endpoints for Main PM<sub>2.5</sub> Benefits Assessments

Endpoint Group	Endpoint Type	Endpoint	Exposure	Ages
Mortality	Mortality	All cause	LT	Adults and older adults (18-99 and 65-99 years)
			ST	Infants (1-12 months)
Cardiovascular Effects	Hospital Admissions	Cardiovascular Outcomes	ST	Older adults (65-99 years)
	Emergency Department Visits	Cardiovascular Outcomes	ST	Children, adults, and older adults (0-99 years)
	Incidence	Acute Myocardial Infarction	ST	Older adults (65-99 years)
		Stroke <sup>a</sup>	LT	Older adults (65-99 years)
		Cardiac Arrest <sup>a</sup>	ST	Children, adults and older adults (0-99 years)
Respiratory Effects	Hospital Admissions	Respiratory Outcomes	ST	Children and older adults (65-99 years)
	Emergency Department Visits	Respiratory Outcomes	ST	Children, adults, and older adults (0-99 years)
	Incidence	Asthma Onset <sup>a</sup>	LT	Children (0-17 years)
		Asthma Symptoms	ST	Children (6-17 years)
		Allergic Rhinitis <sup>a</sup>	LT	Children (3-17 years)
		Minor Restricted Activity Days	NA	Adults and older adults (18-64 years)
		Work Loss Days	NA	Adults and older adults (18-64 years)
Cancer	Incidence	Lung Cancer <sup>a</sup>	LT	Adults and older adults (30-99 years)
Nervous System Effects	Hospital Admissions	Alzheimer's Disease <sup>a</sup>	LT	Older adults (65-99 years)
		Parkinson's Disease <sup>a</sup>	LT	Older adults (65-99 years)

<sup>a</sup>New health endpoint.

### 2.4.1.2 O<sub>3</sub>

Table 9. Set of Health Endpoints for Main O<sub>3</sub> Benefits Assessments

Endpoint Group	Endpoint Type	Specific Endpoint	Exposure	Ages	
Mortality	Mortality	Respiratory <sup>a</sup>	ST	Children, adults, and older adults (0-99 years)	
			LT	Adults and older adults (30-99 years)	
Respiratory Effects	Hospital Admissions	Respiratory Outcomes	ST	Older adults (65-99 years)	
	Emergency Department Visits	Respiratory Outcomes	ST	Children, adults, and older adults (0-99 years)	
	Incidence		Asthma Onset <sup>a</sup>	LT	Children (0-17 years)
			Asthma Symptoms	ST	Children (5-17 years)
			Allergic Rhinitis <sup>a</sup>	LT	Children (3-17 years)
			Minor Restricted Activity Days	ST	Adults and older adults (18-64 years)
			School Loss Days	ST	Children (5-12 years)
				ST	Children (9-10 years)

<sup>a</sup>New or updated health endpoint.

### 2.4.2 Risk Estimates

This section presents the risk estimates identified for the main PM<sub>2.5</sub> (section 2.4.2.1) and O<sub>3</sub> (section 2.4.2.2) benefits assessments. These lists reflect the application of the available epidemiologic literature (section 2.2) to the identification criteria (section 2.1).

#### 2.4.2.1 PM<sub>2.5</sub>

Table 10. Set of Risk Estimates for Main PM<sub>2.5</sub> Benefits Assessments

Endpoint	Study Information	Ages	Exposure Duration	Beta Coefficient (SE) <sup>1</sup>
Mortality	(Wu, Braun et al. 2020)	Older adults (65-99 years)	LT	$\beta = 0.0064$ (0.0003)
	(Pope III, Lefler et al. 2019)	Adults (18-99 years)	LT	$\beta = 0.0113$ (0.0016)
	(Turner, Jerrett et al. 2016)	Adults (30-99 years)	LT	$\beta = 0.0058$ (0.0010)
	(Woodruff, Darrow et al. 2008)	Infants (1-12 months)	LT	$\beta = 0.0056$ (0.00454)
Hospital Admissions, Cardiovascular	(Bell, Son et al. 2015) —ICD 410, omitting 410.x2; 410-414; 426-427; 428; 429; 430-438; and 440-448	Older adults (65-99 years)	ST	$\beta = 0.00065$ (0.00009)
Emergency Department	(Ostro, Malig et al. 2016)—ICD 390-459	Children, adults, and	ST	$\beta = 0.00061$ (0.00042)

Endpoint	Study Information	Ages	Exposure Duration	Beta Coefficient (SE) <sup>1</sup>
Visits, Cardiovascular		older adults (0-99 years)		
Acute Myocardial Infarction	(Wei, Wang et al. 2019)	Adults and older adults (18-99 years)	ST	$\beta = 0.02412$ (0.00928)
Cardiac Arrest	(Ensor, Raun et al. 2013) (Rosenthal, Carney et al. 2008) (Silverman, Ito et al. 2010)	Adults and older adults (0-99 years)	ST	$\beta = 0.00638$ (0.00282) $\beta = 0.00198$ (0.00502) $\beta = 0.00392$ (0.00222)
Stroke	(Kloog, Coull et al. 2012)—ICD 430-436	Older adults (65-99 years)	LT	$\beta = 0.00343$ (0.00127)
Hospital Admissions, Respiratory	(Bell, Son et al. 2015)—ICD 490-492, 464-466, 480-487, 493	Older adults (65-99 years)	ST	$\beta = 0.00025$ (0.00012)
	(Ostro, Roth et al. 2009)—ICD 460-519	Children (0-18 years)	ST	$\beta = 0.00275$ (0.00077)
Emergency Department Visits, Respiratory	(Krall, Anderson et al. 2013)—ICD 480-486, 491, 492, 496, 460-465, 466, 477, 493, 786.07	Children, adults, and older adults (0-99 years)	ST	$\beta = 0.00055$ (0.00027) (GA) $\beta = 0.00097$ (0.00035) (AL) $\beta = 0.00083$ (0.00033) (MO) $\beta = 0.00135$ (0.00059) (TX)
Asthma Onset	(Tetreault, Doucet et al. 2016)	Children (0-17 years)	LT	$\beta = 0.04367$ (0.00088)
Allergic Rhinitis	(Parker, Akinbami et al. 2009)	Children (3-17)	LT	$\beta = 0.02546$ (0.00962)
Lung Cancer	(Gharibvand, Shavlik et al. 2017)	Adults and older adults (>29 years)	LT	$\beta = 0.03784$ (0.01312)
Alzheimer's Disease	(Kioumourtzoglou, Schwartz et al. 2016)—ICD 331.0	Older adults (>64 years)	LT	$\beta = 0.13976$ (0.01775)
Parkinson's Disease	(Kioumourtzoglou, Schwartz et al. 2016)—ICD 332	Older adults (>64 years)	LT	$\beta = 0.07696$ (0.01891)
Asthma Symptoms	(Rabinovitch, Strand et al. 2006)	Children (6-17 years)	ST	$\beta = 0.00200$ (0.00148)
Minor Restricted Activity Days	(Ostro and Rothschild 1989)	Adults and older adults (18-64 years)	N/A	$\beta = 0.00741$ (0.0007)
Work Loss Days	(Ostro 1987)	Adults and older adults (18-64 years)	N/A	$\beta = 0.0046$ (0.00036)

ST- short-term; LT- long-term,  $\beta$ - beta risk estimate; ICD- International Statistical Classification of Diseases

Notes: Horizontal lines separating studies within an endpoint indicates that the studies are not intended to be pooled.

<sup>1</sup> Risk estimates have been mathematically converted to beta coefficients, which include the increment of pollutant change and allow for more direct comparisons of risk estimates within health endpoints.

### 2.4.2.2 O<sub>3</sub>

Table 11. Set of Risk Estimates for Main O<sub>3</sub> Benefits Assessments

Endpoint	Study Information	Ages	Exposure (Duration; Season; Metric)	Beta Coefficient (SE) <sup>1</sup>
Respiratory Mortality	(Zanobetti and Schwartz 2008)	Children, adults, and older adults (0-99 years)	ST; June-August; DA8	$\beta = 0.00083$ (0.00023) (warm season)
	(Katsouyanni, Samet et al. 2009)	Children, adults, and older adults (0-99 years)	ST; April-September; MDA1	$\beta = 0.00073$ (0.00057) (warm season)
	(Turner, Jerrett et al. 2016)—ICD 460-519	Adults and older adults (30-99 years)	LT; April-September; MDA8	$\beta = 0.007696$ (0.00118) (warm season)
Hospital Admissions, Respiratory	(Katsouyanni, Samet et al. 2009)—ICD 460–519	Older adults (65-99 years)	ST; April-September; MDA1	$\beta = 0.00028$ (0.00018) (warm season)
Emergency Department Visits, Respiratory	(Barry, Klein et al. 2019)—ICD 493, 786.07, 460-466, 477, 491, 492, 496, 480–486, 466.1, 466.11, 466.19	Children, adults, and older adults (0-99 years)	ST; January-December; MDA8	$\beta = 0.00118$ (0.00040) (Atlanta, GA) $\beta = 0.00118$ (0.00059) (Birmingham, AL) $\beta = 0.00195$ (0.00049) (Dallas, TX) $\beta = 0.00118$ (0.00040) (Pittsburgh, PA) $\beta = 0.00079$ (0.00030) (St. Louis, MO-IL)
Asthma Onset	(Tetreault, Doucet et al. 2016)	Children (0-17 years)	LT; June-August; MDA8	$\beta = 0.02075$ (0.00146) (warm season)
Asthma Symptoms	(Lewis, Robins et al. 2013)	Children (5-17 years)	ST; January-December; MDA8	$\beta = 0.00708$ (0.00372) (Cough) $\beta = 0.00764$ (0.00410) (Wheeze) $\beta = 0.01140$ (0.00505) (Chest tightness) $\beta = 0.00423$ (0.00386) (Shortness of breath)
Allergic Rhinitis	(Parker, Akinbami et al. 2009)	Children (3-17 years)	LT; May-September; DA24	$\beta = 0.01655$ (0.00390) (warm season)
Minor Restricted Activity Days	(Ostro and Rothschild 1989) (MRADs)	Adults and older adults (18-64 years)	ST; April-September; MDA1	$\beta = 0.0022$ (0.000658)

School Loss Days	(Gilliland, Berhane et al. 2001)	Children (5-17 years)	ST; January-June; DA8	$\beta = 0.0078$ (0.0044)
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ST- short-term; LT- long-term,  $\beta$ - risk estimate (beta); ICD- International Statistical Classification of Diseases; DA8- daily 8-hour average; MDA8- maximum daily 8-hour average; MDA1- maximum daily 1-hour average; DA24- daily 24-hour average

Notes: Horizontal lines separating studies within an endpoint indicates that the studies are not intended to be pooled

<sup>1</sup> Risk estimates have been mathematically converted to beta coefficients, which include the increment of pollutant change and allow for more direct comparisons risk estimates within health endpoints.



### 3 BASELINE INCIDENCE AND PREVALENCE ESTIMATES

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A baseline incidence rate is an estimate of the number of new cases in the assessment location over a specific timespan, typically one year. For example, in 2018 the mortality rate was 868 deaths per 100,000 people in the U.S.<sup>53</sup> The baseline incidence of the health effect is necessary to convert the relative risk of a health effect provided by epidemiologic studies into an estimated number of cases. To derive the total baseline incidence per year, this rate must be multiplied by the corresponding population. Continuing with the above example, there were 327 million people in the U.S. in 2018, leading to a total baseline incidence of 2.8 million deaths in that year.

Prevalence rates are the proportion of the population experiencing a health endpoint at a point in time. This rate is important when estimating impacts of chronic illnesses, such as asthma, in order to exclude those already diagnosed from the population at risk. For example, if the prevalence of asthmatic children is 8%, only the remaining 92% are at risk of developing asthma.

EPA develops either daily or annual baseline incidence and prevalence rates at the most geographically- and age-specific levels feasible for each health endpoint assessed. For many locations within the U.S., these data are available resolved at the county- or state-level, providing a better characterization of the geographic distribution of hospital and emergency department visits than the national rates. For this update, we focused on developing baseline incidence rates for new health endpoints. Detailed information on baseline incidence data developed previously can be found in Appendix D of the BenMAP-CE User Manual ((U.S. EPA 2018)). Importantly, when applying either the daily or annual baseline incidence rates to a health impact estimate, the temporal scale over which the health endpoint was assessed within each study is taken into account. For example, if a long-term O<sub>3</sub> exposure study associated annual deaths with warm-season exposures, full-year baseline incidence rates will be used when estimating benefits.<sup>54</sup>

Table 12 summarizes the sources of baseline incidence rates and provides national average (where used) incidence rates for the endpoints included in the analysis. For both baseline incidence and prevalence data, we used age-stratified rates where available. We applied risk estimates to individual age groups and then sum them over the relevant age range to estimate total population benefits. In some cases, we used a single national incidence rate, due to a lack of more spatially disaggregated data, time, or resources. In these cases, whenever possible we used national average rates, because these data are most applicable to a national assessment of benefits. For some studies, however, the only available incidence information comes from the studies themselves; in these cases, incidence in the study population is assumed to represent typical incidence at the national level.

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<sup>53</sup> CDC WONDER mortality data; <https://www.cdc.gov/nchs/fastats/deaths.htm>.

<sup>54</sup> Turner, M. C., M. Jerrett, A. Pope, III, D. Krewski, S. M. Gapstur, W. R. Diver, B. S. Beckerman, J. D. Marshall, J. Su, D. L. Crouse and R. T. Burnett (2016). "Long-term ozone exposure and mortality in a large prospective study." *American Journal of Respiratory and Critical Care Medicine* **193**(10): 1134-1142. and Tetreault, L. F., M. Doucet, P. Gamache, M. Fournier, A. Brand, T. Kosatsky and A. Smargiassi (2016). "Childhood Exposure to Ambient Air Pollutants and the Onset of Asthma: An Administrative Cohort Study in Quebec." *Environ Health Perspect* **124**(8): 1276-1282. risk estimates of long-term O<sub>3</sub>-attributable health impacts use full-year baseline incidence rates, even though the exposure period is restricted to the warm season. As such, our baseline incidence rate estimates also reflect the full year for those health endpoints.

Table 12. Baseline Incidence Rates for Use in Impact Functions

Endpoint	Parameter	Rates	
		Value	Source
Mortality <sup>1</sup>	Daily or annual projected incidence to 2060 in 5-year increments (0--99)	Age-, cause-, race-, and county-stratified rates	CDC WONDER (2012–2014) (U.S. Census Bureau 2012)
Hospitalizations <sup>2</sup>	Daily incidence rates for all ages	Age-, region/state/county-, and cause- stratified rates	2011-2014 HCUP data files and data requested from and supplied by individual states
Emergency Department Visits <sup>2</sup>	Daily emergency department visit incidence rates for all ages	Age-, region-, state-, county-, and cause-stratified rates	2011-2014 HCUP data files and data requested from and supplied by individual states
Nonfatal Acute Myocardial Infarction	Daily nonfatal AMI incidence rate per person aged 18-99	Age-, region-, state-, and county- stratified rates	(AHRQ 2016)
Asthma Symptoms	Daily incidence among asthmatic children  Wheeze (ages 5-12) Cough (ages 5-12) Shortness of breath (ages 5-12) Albuterol use (ages 6-13)	Age- and race- stratified rates  2.2 puffs per day	(Ostro, Lipsett et al. 2001)  (Rabinovitch, Strand et al. 2006)
Asthma Onset	Annual incidence 0 - 4 5 - 11 12 - 17	0.0234 0.0111 0.0044	(Winer, Qin et al. 2012)
Alzheimer’s Disease	Daily incidence rates for all ages	Age-, region-, state-, and county- stratified rates	2011-2014 HCUP data files
Parkinson’s Disease	Annual incidence 18 - 44 45 - 64 65 - 84 85 - 99	0.0000011 0.0000366 0.0002001 0.0002483	HCUPnet

Endpoint	Parameter	Rates	
		Value	Source
Allergic Rhinitis	Respondents aged 3-17 experiencing allergic rhinitis/hay fever symptoms within the year prior to the survey	0.192	(Parker, Akinbami et al. 2009)
Cardiac Arrest	Daily nonfatal incidence rates 0 - 17 18 - 39 40 - 64 65 - 99	0.00000002 0.00000009 0.00000056 0.00000133	(Rosenthal, Carney et al. 2008, Silverman, Ito et al. 2010, Ensor, Raun et al. 2013)
Lung Cancer	Annual nonfatal incidence 25 - 34 35 - 44 45 - 54 55 - 64 65 - 74 75 - 84 95 - 99	0.000001746 0.000014919 0.000067463 0.000208053 0.000052370 0.000576950 0.000557130	(SEER 2015) and (Gharibvand, Shavlik et al. 2017)
Stroke	Annual nonfatal incidence in ages 65-99	0.00446	(Kloog, Coull et al. 2012)
Work Loss Days	Daily incidence rate per person (18–64) Aged 18–24 Aged 25–44 Aged 45–64	0.00540 0.00678 0.00492	(Adams, Hendershot et al. 1999), Table 41; (U.S. Census Bureau 2000)
School Loss Days	Rate per person per year, assuming 180 school days per year	9.9	(Adams, Hendershot et al. 1999), Table 47
Minor Restricted-Activity Days	Daily MRAD incidence rate per person (18-64)	0.02137	(Ostro and Rothschild 1989), p. 243

CDC-Centers for Disease Control; NHS-National Health Interview Survey

<sup>1</sup>Mortality rates are only available in 5-year increments. The Healthcare Cost and Utilization Program (HCUP) database contains individual level, state and regional-level hospital and emergency department discharges for a variety of International Classification of Diseases (ICD) codes ((AHRQ 2016)).

<sup>2</sup>Baseline incidence rates now include corrections from the states of Indiana and Montana.

### 3.1 MORTALITY

Baseline incidence rate estimates for mortality remain the same as they were for previous benefits assessments ((U.S. EPA 2018)). However, information is provided below for reference. Notably, the (Turner, Jerrett et al. 2016) analysis of long-term O<sub>3</sub>-attributable health impacts compares warm-season exposures to full-year baseline incidence rates. As such our baseline incidence rate estimates also reflect the full year.

### 3.1.1 Mortality Data for 2012-2014

We obtained county-level mortality and population data from 2012-2014 for 11 causes for the contiguous United States by downloading the data from the Centers for Disease Control (CDC) WONDER database.<sup>55</sup>

Since the detailed mortality data obtained from CDC do not include population, we combined them with U.S. Census Bureau population estimates exported from BenMAP. We then generated age-, cause-, and county-specific mortality rates using the following formula:

$$R_{i,j,k} = \frac{D_{i,j,k}(2012)+D_{i,j,k}(2013)+D_{i,j,k}(2014)}{P_{i,k}(2012)+P_{i,k}(2013)+P_{i,k}(2014)}$$

where  $R_{i,j,k}$  is the mortality rate for age group  $i$ , cause  $j$ , and county  $k$ ;  $D$  is the death count; and  $P$  is the population. Additional details about the translation of the CDC WONDER data to age-, cause-, and county-specific mortality rates are provided in the BenMAP-CE User's Manual ((U.S. EPA 2018)).

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<sup>55</sup> <http://wonder.cdc.gov>

Table 13. National Mortality Rates (per 100 people per year) by Health Endpoint and Age Group, 2012-2014

Mortality Category	ICD-10 Codes	Infant*	1-17	18-24	25-34	35-44	45-54	55-64	65-74	75-84	85+
Mortality, All Cause	All	0.59396	0.01951	0.07804	0.10665	0.17264	0.40542	0.86162	1.79670	4.62837	13.58034
Mortality, Non-Accidental	A00-R99	0.55495	0.00949	0.01874	0.04112	0.10876	0.33084	0.79395	1.73208	4.49595	13.20867
Mortality, Respiratory	J00-J98	0.01297	0.00102	0.00127	0.00253	0.00570	0.02013	0.06560	0.20585	0.57827	1.42362
Mortality, Chronic Lung	J40-J47, J67	0.00053	0.00032	0.00040	0.00074	0.00186	0.01033	0.04045	0.13873	0.36008	0.68593
Mortality, Lung Cancer	C34	0.00002	0.00001	0.00007	0.00033	0.00282	0.02378	0.07992	0.19701	0.32952	0.31820
Mortality, Ischemic Heart Disease	I20-I25	0.00033	0.00004	0.00039	0.00234	0.01242	0.04854	0.12174	0.25698	0.68000	2.27271
Mortality, Cardio-Pulmonary	I00-I78, J10-J18, J40-J47, J67	0.00539	0.00069	0.00099	0.00214	0.00502	0.01794	0.05877	0.18453	0.51055	1.26213
Mortality, NCD + LRI	**	0.18459	0.00618	0.01168	0.02751	0.08129	0.26214	0.63767	1.37694	3.44731	9.47467
Mortality, Lower Respiratory Infection	A48.1, A70, B97.4-B97.6, J09-J15.8, J16, J20-J21, P23.0-P23.4, U04	0.00269	0.00618	0.01168	0.00030	0.00062	0.00112	0.00196	0.00300	0.00758	0.02693
Mortality, Cerebro-vascular	G45-G46.8, I60-I63.9, I65-I66.9, I67.0-I67.3, I67.5-I67.6, I68.1-I68.2, I69.0-I69.3	0.00116	0.00012	0.00034	0.00096	0.00314	0.00809	0.01455	0.02892	0.08553	0.20863
Mortality, COPD	J40-J44, J47	0.00048	0.00005	0.00004	0.00015	0.00102	0.00904	0.03888	0.13689	0.35661	0.67457

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

\*\*For a full list of codes for non-communicable diseases (NCD) and lower respiratory infections (LRI), see the IHME GBD Code mapping: <http://ghdx.healthdata.org/record/ihme-data/gbd-2017-cause-icd-code-mappings>.

### 3.1.2 Mortality Rate Projections 2015-2060

To estimate age- and county-specific mortality rates in years 2015 through 2060, we calculated annual adjustment factors, based on a series of Census Bureau projected national mortality rates (for all- cause mortality), to adjust the age-, county-, and cause-specific mortality rates calculated using 2012-2014 data as described above.<sup>56</sup> We used the following procedure:

For each age group, we obtained the series of projected national mortality rates from 2013 to 2050 (see the 2013 rate in Table 14) based on Census Bureau projected life tables.

We then calculated, separately for each age group, the ratio of Census Bureau national mortality rate in year Y (Y = 2014, 2015, ..., 2060) to the 2013 rate, which is assumed to be representative of the 2012-2014 data and used for the base “year.” These ratios are shown for selected years in Table 15.

Finally, to estimate mortality rates in year Y (Y = 2015, 2020, ..., 2060) that are both age-group-specific and county-specific, we multiplied the county- and age-group-specific mortality rates for 2012-2014 by the appropriate ratio calculated in the previous step. For example, to estimate the projected mortality rate in 2015 among ages 18-24 in Wayne County, MI, we multiplied the mortality rate for ages 18-24 in Wayne County in 2012-2014 by the ratio of Census Bureau projected national mortality rate in 2015 for ages 18-24 to Census Bureau national mortality rate in 2013 for ages 18-24.

Table 14. All-Cause Mortality Rate (per 100 people per year), by Source, Year, and Age Group

Source and Year	Infant	1-17	18-24	25-34	35-44	45-54	55-64	65-74	75-84	85+
Calculated CDC 2012-2014	0.594 <sup>1</sup>	0.020	0.078	0.107	0.173	0.405	0.862	1.797	4.628	13.580
Census Bureau 2013 <sup>2</sup>	0.654	0.029	0.088	0.102	0.183	0.387	0.930	2.292	5.409	13.091

<sup>1</sup>The Census Bureau estimate is for all deaths in the first year of life. EPA benefits assessments uses post-neonatal mortality (deaths after the first month, i.e., 0.23 per 100 people) because the health impact function (see Appendix E) estimates post-neonatal mortality. For comparison purpose, we also calculated the rate for all deaths in the first year, which is 0.684 per 100 people.

<sup>2</sup>For a detailed description of the model, the assumptions, and the data used to create Census Bureau projections, see the working paper, “Methodology and Assumptions for the 2012 National Projections,” which is available on <http://www.census.gov/population/projections/files/methodology/methodstatement12.pdf>

<sup>56</sup> All-cause mortality projections are applied to each cause-specific mortality rate.

Table 15. Ratio of Future Year All-Cause Mortality Rate to 2013 Estimated All-Cause Mortality Rate, by Age Group

Year	Infant	1-17	18-24	25-34	35-44	45-54	55-64	65-74	75-84	85+
2015	0.93	0.93	0.96	1.02	0.96	0.96	1.01	1.02	1.03	1.00
2020	0.94	0.94	0.98	1.04	0.97	0.98	1.02	1.03	1.03	1.00
2025	0.85	0.81	0.74	0.80	0.75	0.77	0.85	0.91	0.93	0.97
2030	0.81	0.75	0.66	0.70	0.67	0.69	0.78	0.86	0.89	0.92
2035	0.76	0.70	0.58	0.62	0.60	0.62	0.71	0.81	0.87	0.87
2040	0.73	0.65	0.51	0.53	0.53	0.56	0.64	0.76	0.84	0.86
2045	0.70	0.60	0.45	0.46	0.46	0.50	0.58	0.71	0.80	0.86
2050	0.67	0.56	0.39	0.40	0.40	0.44	0.53	0.66	0.77	0.87
2055	0.64	0.52	0.34	0.35	0.35	0.39	0.48	0.62	0.73	0.88
2060	0.61	0.48	0.30	0.30	0.31	0.34	0.43	0.58	0.70	0.87

### 3.1.3 Race- and Ethnicity-Stratified Incidence Rates

To estimate race-stratified and age-stratified all-cause and respiratory mortality incidence rates at the county level, data from 2007 to 2016 was downloaded from the CDC WONDER mortality database with and without the ‘Hispanic Origin’ disaggregation for two age groups: >25 and <25.<sup>57</sup> The average race rates were calculated for the 10-year timespan before the death/incidence rate for race combinations were back calculated. Correction ratios were calculated for the Hispanic and non-Hispanic rates of each region/race (e.g., (Black - Hispanic) / (Black - All) = Hispanic correction factor and (Black - non-Hispanic) / (Black - All) = non-Hispanic correction factor). The age-group Hispanic and Non-Hispanic correction factors were then applied to the existing, county-level race-stratified baseline incidence rates for all-cause mortality in BenMAP-CE.

#### 3.1.3.1 Race-Stratified Incidence Rates

To estimate race-stratified and age-stratified all-cause and respiratory mortality incidence rates at the county level, we downloaded data from 2007 to 2016 from the CDC WONDER mortality database.<sup>58</sup> Race-stratified incidence rates were calculated for the following age groups: < 1 year, 1- 4 years, 5-14 years, 15-24 years, 25-34 years, 35-44 years, 45-54 years, 55-64 years, 65-74 years, 75-84 years, and 85+ years. To address the frequent county-level data suppression for race-specific death counts, we stratified the county-level data into two broad race categories, White and Non-White populations. In a later step, we stratified the non-White incidence rates by race (Black, Asian, American Indian) using the relative magnitudes of incidence values by race at the regional level, described in more detail below.

We followed the methods outlined in Section D.1.1 of the BenMAP User Manual with one notable difference in methodology; we included an intermediate spatial scale between county and state for imputation purposes ((U.S. EPA 2018)). We designated urban and rural counties within each state using CDC WONDER and, where possible, imputed missing data using the state-urban and state-rural

<sup>57</sup> <http://wonder.cdc.gov>

<sup>58</sup> <http://wonder.cdc.gov>

classifications before relying on broader statewide data. We followed methods for dealing with suppressed and unreliable data at each spatial scale as described in Section D.1.1.

A pooled non-White incidence rate masks important differences in mortality risks by race. To estimate county-level mortality rates by individual race (Black, Asian, American Indian), we applied regional race-specific incidence relationships to the county-level pooled non-White incidence rates. We calculated a weighted average of race-specific incidence rates using regional incidence rates for each region/age/race group normalized to one reference population (the Asian race group) and county population proportions based on race-specific county populations from CDC WONDER where available. In cases of population suppression across two or more races per county, we replaced all three race-specific population proportions derived from CDC WONDER with population proportions derived from 2010 Census data in BenMAP-CE (e.g., 50 percent Black, 30 percent Asian, 20 percent American Indian).

### 3.1.3.2 *Ethnicity-Stratified Incidence Rates*

To estimate ethnicity-stratified and age-stratified all-cause and respiratory mortality incidence rates at the county level, we downloaded data from 2007 to 2016 from the CDC WONDER mortality database.<sup>59</sup> Ethnicity-stratified incidence rates were calculated for the following age groups: < 1 year, 1–4 years, 5–14 years, 15–24 years, 25–34 years, 35–44 years, 45–54 years, 55–64 years, 65–74 years, 75–84 years, and 85+ years. We stratified county-level data by Hispanic origin (Hispanic and non-Hispanic). We followed the methods outlined in Section D.1.1 to deal with suppressed and unreliable data ((U.S. EPA 2018)). We also included an intermediate spatial scale between county and state designating urban and rural counties for imputation purposes, described in detail in Section D.1.3 of the BenMAP User Manual.

## 3.2 HOSPITALIZATIONS

The approach for estimating hospitalization baseline incidence rates for new health endpoints is based on HCUP data, developed to match the granularity and timeframe of other hospitalization endpoints used in benefits assessments. New hospitalization endpoints are comprised of new sets of ICD-9 codes that correspond to newer studies evaluating air pollution-attributable hospitalizations. Detailed information is provided below and available in the BenMAP-CE User Manual ((U.S. EPA 2018)).

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

The level of hospitalization data available differs by state. While many states provide granular discharge-level data, others may only provide county- or state level-data. Also, 14 states, mostly in the southeast, do not provide data to HCUP. For these states, regional statistics from HCUPnet<sup>60</sup> were used to estimate baseline hospitalization rates.

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<sup>59</sup> <https://wonder.cdc.gov/>

<sup>60</sup> HCUPnet is a free, on-line query system based on data from HCUP. It provides access to summary statistics at the state, regional and national levels.



HCUP categorizes hospital admissions in various ways. Hospitalization admission types used when reporting data to HCUP include emergency (admitted from the emergency department), urgent (admitted from another hospital), elective (admitted from another health facility, including long-term care), newborn (admitted for delivery), trauma (not used by all states), and other/missing/invalid. As PM<sub>2.5</sub> and O<sub>3</sub> exposure predominantly leads to cardiovascular and respiratory health effects, we provide some information on the proportion of these types of hospitalizations, based on an analysis of hospitalizations from the state of Florida in 2014. Florida was selected for this analysis as it was the most populated state providing details regarding hospital admission type.

- Emergency hospital admissions comprise approximately 80% of cardiovascular and 85% of respiratory admissions
- Urgent hospital admissions comprise approximately 10% of cardiovascular and 8% of respiratory admissions
- Elective hospital admissions comprise approximately 10% of cardiovascular and 7% of respiratory admissions
- Newborn hospital admissions comprise no cardiovascular and respiratory admissions
- Trauma hospital admissions comprise approximately 0.1% of cardiovascular and respiratory admissions
- Other/missing/invalid hospital admissions comprise no cardiovascular or respiratory admissions

All hospital admission baseline incidence data used in this analysis (and input into BenMAP-CE) reflects total hospital admissions, due to time constraints limiting the ability to separate types (e.g., emergency, urgent, elective, etc) within HCUP data by various states and regions. However, the breakdown of hospital admission types generally reflects the types of health endpoints associated with air pollution exposures, with the majority of effects falling into the emergency and urgent types (e.g., heart or asthma attack) with a small subset potentially leading to elective hospital admissions (e.g., exacerbation of heart failure).

Health endpoints in hospitalization studies are defined using different combinations of ICD codes corresponding to specific diagnoses. Some span large categories of diagnoses, such as all cardiovascular or all respiratory admissions, while others reflect specific conditions, including Alzheimer's disease and Parkinson's disease.<sup>61</sup> For each ICD code combination, unique baseline incidence rates are developed.

In this TSD update, adjustments were made to three existing hospital admission sensitivity endpoints:

***Myocardial Infarction (ICD Codes 410.X0 and 410.X1)***

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<sup>61</sup> Parkinson's disease incidence rates were developed in a slightly different manner, due to time and resource limitations. We develop regional and age-specific incidence rates for Parkinson's disease hospital admissions using the HCUPnet SID, which provides the total number of hospital visits in the U.S. by age group and region, separately. We first calculate the distribution of annual hospital visits across HCUPnet's 6 age groups: less than 1, 1 to 17, 18 to 44, 45 to 64, 65 to 84, and above 85 years old. Since Parkinson's disease typically affects older adults, hospitalization counts are unavailable for the age groups below 18 years old. We apply the national age distribution to the regional hospitalization totals to estimate the annual number of hospital visits by region and age. We then divide the regional and age-specific counts by the regional and age-specific population and by 365 to calculate the daily incidence rates. To generate county level incidence rates, we assume that each county has the same incidence rate as the region it falls within.

Using data from the Healthcare Cost and Utilization Project (HCUPnet), Hospital Inpatient National Statistics, we downloaded the 2014 national estimates of discharge rates per 100,000 people for the set of ICD-9 codes associated with myocardial infarction in BenMAP (410) and the set of ICD-9 codes associated with myocardial infarction in (Danesh Yazdi, Wang et al. 2021) (410.X0, 410.X1). We applied the ratio of (national discharge rates<sub>ICD-9 = 410.X0, 410.X1</sub> : national discharge rates<sub>ICD-9 = 410</sub>), 0.995, to the existing, county-level baseline incidence rates for Acute Myocardial Infarction, Nonfatal in BenMAP.

#### ***Ischemic Stroke (ICD Codes 433.X1, 434.X1, and 436)***

Using data from the Healthcare Cost and Utilization Project (HCUPnet), Hospital Inpatient National Statistics, we downloaded the 2014 national estimates of discharge rates per 100,000 people for the set of ICD-9 codes associated with stroke in BenMAP (431-437) and the set of ICD-9 codes associated with ischemic stroke in (Danesh Yazdi, Wang et al. 2021) (433.X1, 434.X1, 436). We applied the ratio of (national discharge rates<sub>ICD-9 = 433.X1, 434.X1, 436</sub> : national discharge rates<sub>ICD-9 = 431-437</sub>), 0.564, to the existing, county-level baseline incidence rates for HA, Stroke in BenMAP.

#### ***Atrial Fibrillation and Flutter (ICD Codes 427.3)***

Using data from the Healthcare Cost and Utilization Project (HCUPnet), Hospital Inpatient National Statistics, we downloaded the 2014 national estimates of discharge rates per 100,000 people for the set of ICD-9 codes associated with dysrhythmia in BenMAP (427) and the set of ICD-9 codes associated with atrial fibrillation and flutter in (Danesh Yazdi, Wang et al. 2021) (427.3). We applied the ratio of (national discharge rates<sub>ICD-9 = 427.3</sub> : national discharge rates<sub>ICD-9 = 427</sub>), 0.666, to the existing, county-level baseline incidence rates for HA, Dysrhythmia in BenMAP.

### **3.3 EMERGENCY DEPARTMENT VISITS**

As new studies evaluating air pollution-attributable emergency department utilizing new sets of ICD-9 codes were identified for use in benefits assessment here, we developed corresponding new emergency department baseline incidence rates. Similar to hospitalization baseline incidence rates, the approach for estimating emergency department visit baseline incidence rates also utilizes HCUP data and remains the same as in previous benefits assessments, details for which can be found in the BenMAP-CE User Manual ((U.S. EPA 2018)). Information is provided below for reference.

Similar to hospitalization rates, the data source for emergency department/room visits is also HCUP, (i.e., SID, SEDD, and NEDS), states vary by level of data provided (i.e., discharge-, county-, state, and regional-level), and unique baseline incidence rates are generated for each health endpoint ICD code combination.

### **3.4 HEALTH ENDPOINT ONSET/OCCURRENCE**

Baseline incidence estimates for health endpoint onset or occurrences are described below, listed in alphabetical order. Onset indicates the development of a health endpoint (e.g., asthma diagnosis), whereas occurrence refers to an instance of that health endpoint (e.g., asthma attack).

### 3.4.1 Acute Myocardial Infarctions (AMIs)

Baseline incidence rate estimates for AMIs remain the same as they were for previous benefits assessments. However, detailed information is provided below for reference.

The relationship between short-term particulate matter exposure and heart attacks was originally quantified in a case-crossover analysis by (Peters, Dockery et al. 2001) and supplemented with evidence found in more recent single and multi-city studies ((Sullivan, Sheppard et al. 2005, Pope III, Muhlestein et al. 2006)). The population in the original study was identified from heart attack survivors in a medical clinic. Therefore, the applicable population to apply to the risk estimate is all individuals surviving a heart attack in a given year. Several data sources are available to estimate the number of heart attacks per year. For example, several cohort studies have reported estimates of heart attack incidence rates in the specific populations under study. However, these rates depend on the specific characteristics of the populations under study and may not be the best data to extrapolate nationally. The American Heart Association reports approximately 785,000 new heart attacks per year ((Roger, Go et al. 2012)). Exclusion of heart attack deaths reported by CDC Wonder yields approximately 575,000 nonfatal cases per year.

An alternative approach to the estimation of heart attack rates is to use data from the Healthcare Cost and Utilization Project (HCUP), assuming that all heart attacks that are not instantly fatal will result in a hospitalization. Details about HCUP data are described in Section D.2 of the BenMAP-CE User Manual ((U.S. EPA 2018)). According to the 2014 HCUP data there were approximately 608,795 hospitalizations due to heart attacks (acute myocardial infarction: ICD-9 410, primary diagnosis). We estimated baseline rates based on HCUP data rather than extrapolating from cohort studies because HCUP is a national database with a larger sample size intended to provide reliable national estimates. The incidence rate calculation is also described in Section D.2 of the BenMAP-CE User Manual and the incidence rates for AMI hospitalization are presented in Table D-5. An alternative approach to the estimation of AMI rates is to use data from HCUP and assume that all AMIs that are not instantly fatal will result in a hospitalization.

It is important to note that when calculating the incidence of nonfatal AMIs, the fraction of fatal heart attacks is subtracted to ensure that there is no double-counting with mortality estimates. Specifically, we apply an adjustment factor in the risk estimate to reflect the probability of surviving a heart attack. The adjustment factor comes from Rosamond et al., 1999, which reported that approximately 6% of male and 8% of female hospitalized AMI patients die within 28 days (either in or outside of the hospital). Therefore, we applied a factor of 0.93 to the estimated number of PM-related AMIs to exclude the number of cases that result in death within the first month. Note that we did not adjust for fatal AMIs in the incidence rate estimation, due to the way that the epidemiological studies are designed. Those studies consider total admissions for AMIs, which includes individuals living at the time the studies were conducted. We use the definition of AMI that matches the definition in the epidemiological studies. Age-specific baseline incidence rates are based on data from the Agency for Healthcare Research and Quality's HCUP NIS database ((AHRQ 2016)). We identified death rates for adults hospitalized with AMI stratified by age (e.g., 1.852% for ages 18-44, 2.8188% for ages 45-64, and 7.4339% for ages 65+). These rates show a clear downward trend over time between 1994 and 2009 for the average adult and thus replace the 93% survival rate previously applied across all age groups from (Rosamond, Broda et al. 1999).

### 3.4.2 Asthma Onset and Symptoms

#### 3.4.2.1 Asthma Onset

Baseline incidence rates for new asthma onset are estimated from (Winer, Qin et al. 2012). (Winer, Qin et al. 2012) identify newly diagnosed asthma from the 2006-2008 Asthma Call-Back Survey (ACBS) and Behavioral Risk Factor Surveillance System (BRFSS) as individuals diagnosed by a doctor, or other health professional, within the 12 months prior to the surveys. Table 12 details the breakdown, by age, of the annual national incidence rates for asthma onset.

For the set of endpoints affecting the asthmatic population, in addition to baseline incidence rates, prevalence rates of asthma in the population are needed to define the applicable population. We derive asthma prevalence data from the National Health Interview Survey (NHIS).<sup>62</sup> For functions with age ranges that do not align with the ranges reported in the NHIS data table, we develop a weighted-average prevalence rate for the age range, where the weights are the number of years that overlap with each NHIS age group. Table 16 provides the breakdown of the 2018 NHIS rates used to calculate the weighted averages. Table 17 details the resulting weighted averages by study and age group. Note that these reflect recent asthma prevalence and assume no change in prevalence rates in future years.

Table 16. Asthma Prevalence Rates

NHIS Age Group	Asthma Prevalence Rate
0 - 4	0.038
5 - 11	0.081
5 - 14	0.086
12 - 17	0.099
15 - 19	0.110
20 - 24	0.081
0 - 17	0.075

Table 17. Weighted Average Asthma Prevalence by Study

Endpoint	Ages	Author <sup>1</sup>	Pollutant	Weighted Prevalence
Asthma Onset	0 – 4	(Tetreault, Doucet et al. 2016)	PM <sub>2.5</sub>	0.0380
	5 - 17	(Tetreault, Doucet et al. 2016)	PM <sub>2.5</sub>	0.0893
	0 - 17	(Tetreault, Doucet et al. 2016)	O <sub>3</sub>	0.0750
Asthma symptoms, albuterol use	6 - 13	(Rabinovitch, Strand et al. 2006)	PM <sub>2.5</sub>	0.0860

<sup>1</sup>Prevalence rate derived for albuterol use must be loaded into BenMAP-CE as part of a separate incidence or prevalence dataset, unlike the remainder of the rates, which are embedded within the health impact functions.

<sup>62</sup> <https://www.cdc.gov/asthma/nhis/2018/data.htm> and [https://www.cdc.gov/asthma/most\\_recent\\_national\\_asthma\\_data.htm](https://www.cdc.gov/asthma/most_recent_national_asthma_data.htm)

### 3.4.2.2 *Albuterol Use*

We develop incidence rates for albuterol use from the rates presented in (Rabinovitch, Strand et al. 2006), the same study from which the risk estimate was developed. As described in the ‘Recommended Set of Health Endpoints and Health Impact Functions’ section, (Rabinovitch, Strand et al. 2006) analyzed the relationship between short-term PM<sub>2.5</sub> exposure and asthma exacerbation in children ages 6 to 13 years old. The authors use an electronic inhaler to record the number of actuations (‘puffs’) for each 24-hour period and calculate an average albuterol use rate of 2.2 ‘puffs’ per child per day.

As described in section 3.4.2.1, in addition to the baseline incidence rates, we apply a weighted-average asthma prevalence rate of 0.086, based on the 5-14 age group, using the NHIS prevalence data to identify the applicable population.

### 3.4.2.3 *Asthma Symptoms*

We develop incidence rates for asthma symptoms using the estimates presented in (Lewis, Robins et al. 2013), the same study from which the concentration-response function was developed. As described in the ‘Recommended Set of Health Endpoints and Health Impact Functions’ section, (Lewis, Robins et al. 2013) studied the effects of short-term O<sub>3</sub> exposure on frequency of asthma symptoms in an asthmatic population of children ages 5 to 12 years old. The authors estimate the incidence of each asthma symptom using the number of person-days where children reported experiencing the symptom divided by the total number of person-days monitored for that symptom. The percent of days monitored during which children experienced each symptom are calculated as 30.1% for cough, 19.4% for wheeze, 18.5% for shortness of breath, and 12.7% for chest tightness. Therefore, the national incidence rates of asthma symptoms are 0.301 for cough, 0.194 for wheeze, 0.185 for shortness of breath, and 0.127 for chest tightness. ‘Prevalence rates for asthma symptoms remains the same as in previous benefits assessments (previously referred to as asthma exacerbation) (Table 16).

### 3.4.3 *Allergic Rhinitis*

We develop prevalence rates for hay fever/rhinitis using the estimates presented in (Parker, Akinbami et al. 2009), the same study from which the concentration-response function was developed. As described in the ‘Recommended set of Health Endpoints and Health Impact Functions’ section, (Parker, Akinbami et al. 2009) investigates the associations between long-term ozone exposure and respiratory allergies in children ages 3 to 17 years old. The authors use prevalence data from the NHIS household interview survey and define allergic rhinitis as children with reported hay fever, respiratory allergy, or both within the 12 months prior to the survey. Of the eligible population (72,279), 19.2% of respondents experience allergic rhinitis symptoms within the year prior to the survey, therefore, the national prevalence rate of hay allergic rhinitis is 0.192.

### 3.4.4 *Lung Cancer*

We use the existent baseline incidence rate for lung cancer mortality in combination with the five-year lung cancer survival rate from (SEER 2015) to develop baseline incidence rates for non-fatal lung cancer. We first use the five-year lung cancer survival rate to calculate the total incidence of lung cancer (both fatal and non-fatal) from the baseline mortality rate using the following formula: baseline mortality rate / (1 – five-year survival rate). We then calculate the incidence of non-fatal lung cancer as the difference between total lung cancer incidence and fatal lung cancer incidence ((SEER 2015)). Table 18 presents the

baseline incidence of lung cancer mortality, the SEER five-year survival rate, the estimated total lung cancer incidence, and the estimated non-fatal lung cancer incidence rate by age group.

Table 18. Lung Cancer Incidence Rates

Age Group	Annual Lung Cancer Mortality Incidence [A]	Five-Year Survival Rate [B]	Total Lung Cancer Incidence [C] = [A] / (1 - [B])	Non-fatal Lung Cancer Incidence [D] = [C] - [A]
25-34	0.0000033	34.6%	0.0000050	0.00000175
35-44	0.0000282	34.6%	0.0000431	0.00001492
45-54	0.0002378	22.1%	0.0003053	0.00006746
55-64	0.0007922	20.8%	0.0010003	0.00020805
65-74	0.00019701	21.0%	0.0002494	0.00005237
75-84	0.0032952	14.9%	0.0038722	0.00057695
85+	0.0031820	14.9%	0.0037391	0.00055713

### 3.4.5 Minor Restricted Activity Days (MRAD)

The incidence estimate for this health endpoint remains the same as in previous benefits assessments. (Ostro and Rothschild 1989) (p. 243) provide an estimate of the annual incidence rate of MRADs per person of 7.8.

### 3.4.6 School Loss Days

Baseline incidence rate estimates for school loss days remain the same as they were for previous benefits assessments. However, detailed information is provided below for reference.

We have two sources of information to use when estimating the baseline incidence rates of missed school days: the National Center for Education Statistics (NCES), which provided an estimate of all-cause school loss days, and the National Health Interview Survey (NHIS) ((NCES 1996, Adams, Hendershot et al. 1999), Table 47), which has data on different categories of acute school loss days. Table 19 presents the estimated school loss day rates. Further detail is provided below on these rates.

Table 19. School Loss Day Rates (per student per year)

Type	Northeast	Midwest	South	West
Respiratory illness-related absences	1.3	1.7	1.1	2.2
Illness-related absences	2.4	2.6	2.6	3.7
All-cause	9.9	9.9	9.9	9.9

\*Illness-related school loss day rates were based on data from the 1996 NHIS and an estimate of 180 school days per year, excluding school loss days due to injuries. All-cause school loss day rates were based on data from the NCES.

#### 3.4.6.1 All-Cause School Loss Day Rate

Based on data from the U.S. Department of Education (1996, Table 42-1), the National Center for Education Statistics estimates that for the 1993-1994 school year, 5.5% of students are absent from school on a given day. This estimate is comparable to study-specific estimates from (Chen, Jennison et al. 2000) and (Ransom and Pope 1992), which ranged from 4.5% to 5.1%.

### 3.4.6.2 *Illness-Related School Loss Day Rate*

The National Health Interview Survey (NHIS) has regional estimates of school loss days due to a variety of acute conditions ((Adams, Hendershot et al. 1999)). NHIS is a nationwide sample-based survey of the health of the noninstitutionalized, civilian population, conducted by NCHS. The survey collects data on acute conditions, prevalence of chronic conditions, episodes of injury, activity limitations, and self-reported health status. However, it does not provide an estimate of all-cause school loss days.

In estimating illness-related school loss days, we started with school loss days due to acute problems ((Adams, Hendershot et al. 1999), Table 47) and subtracted lost days due to injuries, in order to match the definition of the study used in the risk estimate to estimate illness-related school absences ((Gilliland, Berhane et al. 2001)). We then divided by 180 school days per to estimate illness-related school absence rates per school day. Similarly, when estimating respiratory illness-related school loss days, we use data from (Adams, Hendershot et al. 1999), Table 47. Note that we estimated 180 school days in a year to calculate respiratory illness-related school absence rates per year.

### 3.4.7 **Work Loss Days**

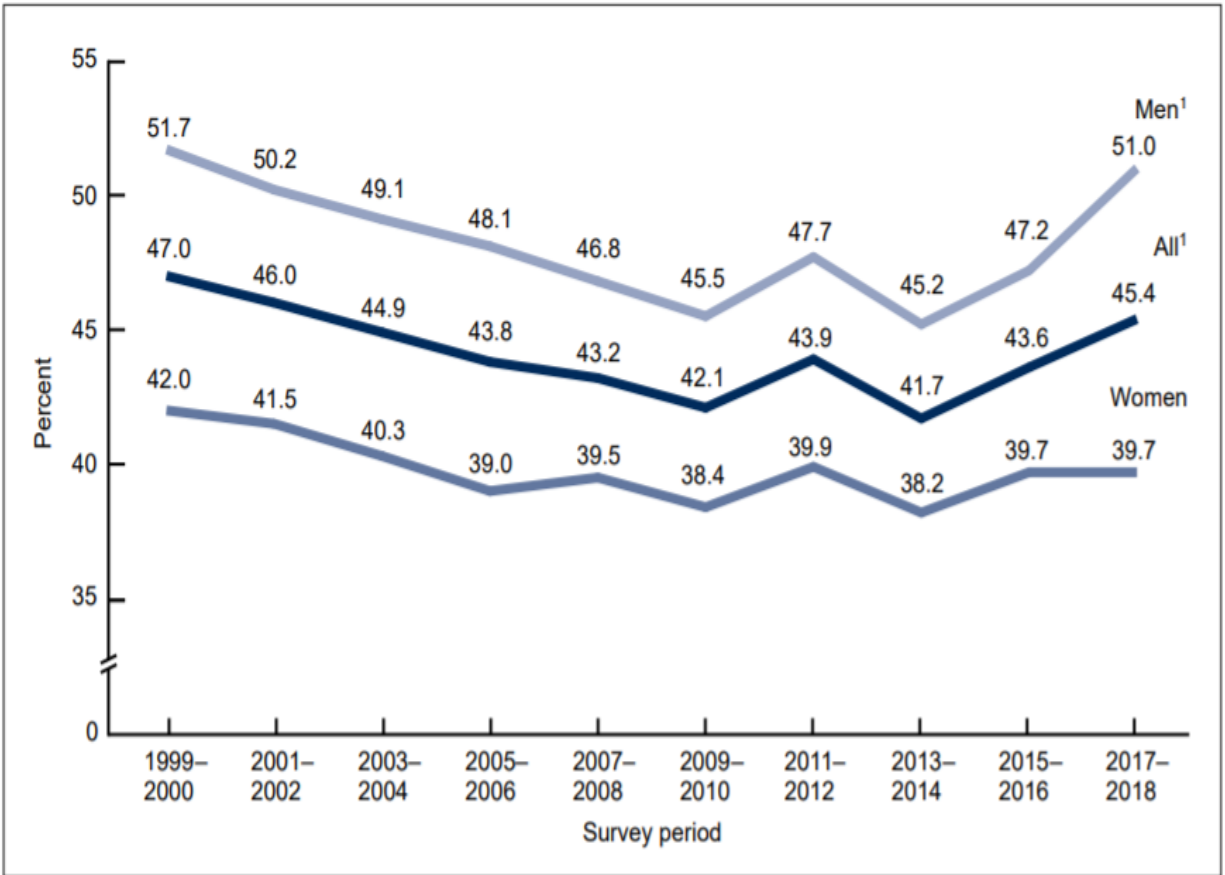
The incidence estimate for this health endpoint remains the same as in previous benefits assessments. The yearly work-loss-day incidence rate per 100 people is based on estimates from the 1996 National Health Interview Survey ((Adams, Hendershot et al. 1999), Table 41). They reported total annual work loss days of 352 million for individuals ages 18 to 65. The total population of individuals of this age group in 1996 (162 million) was obtained from ((U.S. Census Bureau 1998)). The average annual rate of work loss days per individual is 2.17. Using a similar approach, we calculated work-loss-day rates for ages 18-24, 25-44, and 45-64, respectively.

### 3.4.8 **Hypertension**

The state-level baseline incidence rates for hypertension among women ages 50-99 were calculated using the following relationship between incidence and prevalence:

$$\frac{\text{Prevalence}}{1 - \text{Prevalence}} = \text{Incidence} * \text{Average Duration of Disease.}$$

This relationship assumes that hypertension prevalence is at a steady state in the population of interest. Data from the National Health and Nutrition Examination Survey supports this assumption, finding no significant change in age-adjusted hypertension prevalence among U.S. women from 1999-2000 to 2017-2018.



<sup>1</sup>Significant quadratic trend from 1999 through 2018.

NOTES: Hypertension is defined as systolic blood pressure greater than or equal to 130 mmHg or diastolic blood pressure greater than or equal to 80 mmHg, or currently taking medication to lower blood pressure. All estimates are age adjusted by the direct method to the U.S. Census 2000 population using age groups 18–39, 40–59, and 60 and over. Access data table for Figure 4 at: <https://www.cdc.gov/nchs/data/databriefs/db364-tables-508.pdf#4>.

SOURCE: NCHS, National Health and Nutrition Examination Survey, 1999–2018.

Figure 11. Age-Adjusted Trend in Hypertension Prevalence Among Adults Aged 18 and Over by Sex in the U.S. Between 1999-2018

We calculated state-level hypertension prevalence rates using data from the Behavioral Risk Factor Surveillance System (BRFSS), a system of health-related telephone surveys administered by the CDC that collects data from all fifty states. We calculated national-level duration of disease using data from the CDC, the Canadian Chronic Disease Surveillance System (CCDSS), and Loukine et al. (2010). In this calculation, we assumed that hypertension, once diagnosed, lasts until death (even if controlled by medication or diet). The definition of hypertension employed by BRFSS (see below) supports this assumption.

The procedure for calculating state-level hypertension prevalence rates is summarized as follows:

- We obtained individual-level records from the 2019 BRFSS Data file for all states except New Jersey, which was not included in the 2019 data file.
- For consistency with the relevant C-R function, we filtered the individual-level 2019 BRFSS dataset to include responses from female participants aged 50 and older.



- We aggregated the resulting sample by state, using raking-derived weights<sup>63</sup> assigned to each respondent by BRFSS. State-level prevalence was calculated as the sum of weights associated with respondents who responded “Yes” to the question, “Have you ever been told by a doctor, nurse, or other health professional that you have high blood pressure?” divided by the sum of weights of all respondents in the state.
- For New Jersey, we repeated the above steps using the 2017 BRFSS Data File, the most recent year available for the state.

The procedure for calculating the national-level duration of disease is summarized as follows:

- For each five-year age group (50-54 years, 55-59 years, 60-64 years, 65-69 years, 70-74 years, 75-79 years, and 80+ years), we estimated duration of disease using the following equation:

$$\text{Duration of disease} = \text{LE}_{\text{All U.S. females}} - (\text{LE}_{\text{All Canadian females}} - \text{LE}_{\text{Canadian females with hypertension}})$$

- We obtained the life expectancy (LE) values from the following sources:
  - We obtained  $\text{LE}_{\text{All U.S. females}}$  from CDC Vital Statistics Rapid Release and applied the life expectancy of the lower bound of each age group (i.e., we applied the life expectancy at age 50 to the 50-54 years age group).
  - We calculated the  $\text{LE}_{\text{All Canadian females}}$  by taking the weighted average of  $\text{LE}_{\text{Canadian females with hypertension}}$  and  $\text{LE}_{\text{Canadian females without hypertension}}$  from Loukine et al. (2010).
    - Weights were derived from hypertension prevalence estimates among Canadian females (aged 50-64, 65-79, and 80+) from CCDSS.
    - We are not aware of any U.S. studies that estimate the change in life expectancy associated with hypertension at 5-year intervals.
  - We obtained  $\text{LE}_{\text{Canadian females with hypertension}}$  from Loukine et al. (2010).
  - In all three instances, LE for the 80+ age group was calculated as the average of LE for the 80-84 and 85+ age groups for consistency with age groups provided by BRFSS.
- We calculated the overall duration of disease for females ages 50-99 by taking the weighted average of the duration of disease values for the five-year age groups.
  - Weights were calculated from the raking-derived weights provided by BRFSS as the fraction of the female hypertensive population aged 50-99 that falls within the given age class.

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<sup>63</sup> “Raking,” or iterative proportional fitting, is the process that BRFSS uses to adjust for demographic differences between the sample surveyed and the U.S. population. Through this process, BRFSS assigns a final, “raking-derived weight” to each respondent that can be used to generate a nationally-representative dataset.

## 4 DEMOGRAPHIC INFORMATION

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Quantified and monetized human health impacts are calculated using information regarding the demographic characteristics of the population exposed to air pollution; these data include the age, sex, race/ethnicity, and location of the population. We use population projections based on economic forecasting models developed by Woods and Poole, Inc. ((Woods & Poole 2015)). The Woods and Poole (WP) database contains county-level projections of population by age, sex, and race out to 2050, relative to a baseline using the 2010 Census data. Projections in each county are determined simultaneously with every other county in the U.S to take into account patterns of economic growth and migration.

The sum of growth in county-level populations is constrained to equal a previously determined national population growth, based on Bureau of Census estimates ((Hollmann, Mulder et al. 2000)). According to WP, linking county-level growth projections together and constraining to a national-level total growth avoids potential errors introduced by forecasting each county independently. County- and tract-level projections are developed in a four-stage process:

1. National-level variables such as income, employment, and populations are forecasted.
2. Employment projections are made for 179 economic areas defined by the Bureau of Economic Analysis (U.S. BEA, 2004), using an “export-base” approach, which relies on linking industrial-sector production of non-locally consumed production items, such as outputs from mining, agriculture, and manufacturing with the national economy. The export-based approach requires estimation of demand equations or calculation of historical growth rates for output and employment by sector.
3. Population is projected for each economic area based on net migration rates derived from employment opportunities and following a cohort-component method based on fertility and mortality in each area.
4. Employment and population projections are repeated for counties, using the economic region totals as bounds. The age, sex, and race distributions for each region or county are determined by aging the population by single year of age by sex and race for each year through 2050 based on historical rates of mortality, fertility, and migration.

Population projections stratified by race/ethnicity, age, and sex are based on economic forecasting models developed by Woods and Poole ((Woods & Poole 2015)). The Woods and Poole database contains county-level projections of population by age, sex, and race out to 2050, relative to a baseline using the 2010 Census data. Population projections for each county are determined simultaneously with every other county in the U.S to consider patterns of economic growth and migration. County-level estimates of population percentages within the poverty status and educational attainment groups were derived from 2015-2019 5-year average ACS estimates. Additional information can be found in Appendix J of the BenMAP-CE User’s Manual (<https://www.epa.gov/benmap/benmap-ce-manual-and-appendices>).

## 5 HEALTH ENDPOINT VALUATION

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To directly compare benefits estimates associated with a rulemaking to cost estimates, the number of instances of each air pollution-attributable health impact must be converted to a monetary value. This requires a valuation estimate for each unique health endpoint, and potentially also discounting if the benefits are expected to accrue over more than a single year, as recommended by the (U.S. EPA 2014).

As reductions in ambient concentrations of air pollution generally lower the risk of future adverse health effects by a small amount for a large population, the most appropriate economic measure is the ex-ante (before the effect has occurred) willingness-to-pay (WTP) for changes in risk. WTP values are calculated by dividing the monetary value an individual is willing to pay for a specific risk reduction by that change in risk.<sup>64</sup> Using this approach, the size of the affected population is automatically taken into account by the number of incidences predicted by epidemiological studies applied to the relevant population. There are four primary components of the value to society of an individual's avoidance of a non-fatal illness: 1) medical costs, 2) lost productivity, 3) cost of caregiving, and 4) impacts on quality of life (i.e., "pain and suffering"). Some health injuries may incur other costs. Estimates of individual WTP are conventionally thought to reflect the total cost to society and are the preferred welfare valuation measure.<sup>65</sup> However, WTP values are available for a very limited subset of health endpoints, such as mortality.<sup>66</sup>

For health endpoints where WTP estimates are not available, such as hospital admissions, we instead use the cost of treating or mitigating the effect to estimate the economic value. Cost-of-illness (COI) estimates are generally considered to be a lower bound estimate of the true value of reducing the risk of a health effect because they reflect the direct expenditures related to treatment and in some cases costs such as associated productivity losses, but not the value of avoided pain and suffering ((Berger, Blomquist et al. 1987, Harrington and Portney 1987, U.S. EPA 2014)). Additionally, COI estimates require additional parsing of individual health endpoints. For example, a stroke may initially involve an emergency department visit and hospitalization, but will also likely include additional follow-up medical costs, such as doctor visits, medications, the cost of caregiving, and the cost of subsequent health injuries due to the stroke (sequella).

To prevent double counting of health impacts, when estimating monetary valuations, health endpoints are separated into the following non-overlapping categories: mortality (section 5.1), hospital admissions, emergency department visits (section 5.2), and health endpoint onset/occurrence (section 5.3).

EPA develops valuation estimates at the most age-refined level feasible for each health endpoint assessed. While we focused on identifying valuation estimates from peer-reviewed and published literature for new health endpoints, we were also able to update several valuation estimates for

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<sup>64</sup> For example, suppose a measure is able to reduce the risk of mortality from 2 in 10,000 to 1 in 10,000 (a reduction of 1 in 10,000). If individual WTP for this risk reduction is \$100, then the WTP for an avoided statistical mortality amounts to \$1 million ( $\$100/0.0001$  change in risk).

<sup>65</sup> WTP estimates may not fully account for medical costs or lost productivity if individuals assume some related costs would be borne by others (e.g., health insurance providers and employers).

<sup>66</sup> Economic theory also argues that WTP for most goods (such as environmental protection) will increase if real income increases.

endpoints evaluated in previous benefits analyses, such as stroke, cardiac arrest, and AMIs. New hospitalizations and emergency department visits health endpoint valuations reflect specific ICD-9 codes evaluated by the epidemiologic study. New onset or follow-up/management health endpoints reflect WTP or COI valuation estimates that exclude death and initial emergency department and hospitalization costs.

These COI measures represent an update to EPA’s previous method to producing COI estimates in three important respects ((U.S. EPA 2018)):

- Estimates are of the *costs* of medical treatment, rather than *charges* by medical providers.
- Sampling parameters are used in survey data to express statistical uncertainty in mean cost estimates.
- More recent data is being used to reflect current treatment and healthcare costs.

When multiple valuation studies are available, the strengths and limitations of each study are considered, in a manner similar to that described for epidemiologic studies (section 2.1). The criteria for evaluation of these studies are listed in Table 20. In some cases, judgment is required to identify studies for valuation estimates when a similar number of preferred attributes are satisfied by multiple studies.

Table 20. Cost of Illness Economic Study Identification Consideration Factors

<b>Criteria<sup>a</sup></b>	<b>Prioritization Detail (In order of most to least preferred)</b>
Peer-Reviewed Research	Peer-reviewed and published literature only
Endpoint Definition	1. ICD codes align with the epidemiological study 2. ICD codes overlap with the epidemiological study
Population Attributes	Prefer studies that match epidemiological study’s population (specifically by age)
Study Period	More recent data are preferred
Measure of Costs <sup>b</sup>	1. Total payments 2. Allowable charges 3. Cost-adjusted charges 4. Unadjusted charges
Study Location	1. Nationwide coverage 2. Multi-city and/or multi-state coverage 3. Local study population
Coverage of cost elements	Studies that account for more cost elements (e.g., treatment settings) and longer time horizons are preferred
Study Size	Larger study size preferred

<sup>a</sup> This table focuses on COI because WTP measures are not currently available for the health endpoints of interest. Had WTP estimates been available, additional criteria would be relevant. It also excludes valuation estimates of hospitalizations and emergency department visits, which are developed by EPA and described in the appendices to (U.S. EPA 2018).

<sup>b</sup>(Onukwugha, McRae et al. 2016) provides more information on these methods.

We provide unit values for health endpoints (along with information on the distribution of the unit value) in Table 21. All values are in constant year 2015\$, adjusted for growth in real income for WTP estimates out to 2024 using projections provided by Standard and Poor’s, which is discussed in further detail below. Additional detail regarding the development of each health endpoint valuation is also

provided below. When possible, costs are separated into components which can be separately adjusted for growth in healthcare costs, income, and other costs. Costs occurring over multiple years are discounted with a constant 2% discount rate.

Table 21. Unit Values for Economic Valuation of Health Endpoints (2015\$)<sup>1</sup>

Health Endpoint	Type	Central Estimate of Value Per Statistical Incidence (2015\$)	Healthcare Costs	Labor Costs	Care and Other Costs	Source
Mortality	Value of Statistical Life (VSL)	Undiscounted: \$8,705,114 2: \$8,132,666				Weibull distribution fitted to 26 published VSL estimates (5 contingent valuation and 21 labor market studies). Underlying studies, distribution parameters, and other information are available in Appendix B of the EPA's <i>Guidelines for Preparing Economic Analyses</i> ((U.S. EPA 2014)). Adjusted for income growth appropriate to the year of analysis.
Hospitalizations	Medical costs and opportunity cost of time	Varies by ICD codes, ranging between \$7,700 and \$16,000				HCUP data (details available in section 3.2)
Emergency Department Visits	Medical costs	Varies by ICD codes, ranging between \$600 and \$1,200				HCUP data (details available in section 3.3)
Nonfatal Myocardial Infarction (AMI) <sup>a</sup>	3-year medical cost <sup>s</sup> (excluding ED and hospitalization) plus lost labor	\$49,108	\$49,108	Multiple of annual earnings		(O'Sullivan, Rubin et al. 2011), Cropper and Krupnick, 1990
Asthma Symptom-Albuterol Use <sup>c</sup>	Medical costs	\$0.35 per albuterol inhaler puff				Average prescription costs derived from Epocrates.com and Goodrx.com accessed March 19, 2020

Asthma Symptom- Chest Tightness, Cough, Shortness of Breath, or Wheeze	WTP for 1 symptom day	\$219			\$219	(Dickie and Messman 2004)
Asthma Onset <sup>c</sup>	Lifetime medical costs and lost productivity	\$182,681	\$93,820	\$85,800	\$3,136	(Maniloff and Fann 2023)
Allergic Rhinitis <sup>c</sup>	1-year medical costs	\$600	\$600			(Soni 2008)
Cardiac Arrest <sup>c</sup>	3-year medical costs	3%: \$36,000 7%: \$35,000				(O'Sullivan, Rubin et al. 2011)
Lung Cancer <sup>c</sup>	5-year medical costs	\$34,000				(Kaye, Min et al. 2018)
Stroke <sup>c</sup>	Lifetime medical costs, care costs, and lost productivity	\$159,067	\$57,330	\$90,039	\$12,044	(Maniloff and Fann 2023)
Work Loss Days	Median daily wage	U.S. mean: \$298		\$298		EPA calculation(IEc 1993)
School Loss Days	Lost productivity of parent and lost learning	\$1186		\$1186		(Liu, Lee et al. 2021), (US Bureau of Labor Statistics 2021), (US Bureau of Labor Statistics 2021), (Chetty, Friedman et al. 2014), (U.S. Census Bureau 2010), (U.S. EPA 2020), (U.S. Census Bureau 2021)
Minor Restricted- Activity Days	Median WTP	\$70			\$70	(IEc 1993)

## 5.1 MORTALITY

Following the advice of the SAB’s Environmental Economics Advisory Committee (SAB-EEAC), the EPA currently uses the value of statistical life (VSL) approach in calculating the core estimate of mortality benefits, because we believe this calculation provides the most reasonable single estimate of an individual’s willingness to trade money for reductions in mortality risk ((Stavins 2000)). The VSL approach is a summary measure for the value of small changes in mortality risk experienced by a large number of people.

### 5.1.1 Value of a Statistical Life (VSL)

The current undiscounted VSL used by EPA is \$8.7 million (2015\$). This estimate is the mean of a distribution fitted to 26 VSL estimates that appear in the economics literature and that have been identified in the Section 812 Reports to Congress as “applicable to policy analysis” ((U.S. EPA 2011)). It is a value EPA uses in RIAs as well as in the Section 812 Retrospective and Prospective Analyses of the Clean Air Act ((U.S. EPA 2011)). For mortality estimates using the 20-year lagged mortality, the present value of the lagged mortality is \$8.1 million (2015\$) when discounting at 2%.

The VSL approach mirrors that of (Viscusi 1992) and uses the same criteria as in his review of value of statistical life studies. The \$8.7 million estimate is consistent with the conclusions of (Viscusi 1992) (updated to 2015\$) that “most of the reasonable estimates of the value of life are clustered in the \$5.2 to \$12.3 million range.” Five of the 26 studies are contingent valuation studies, which directly solicit WTP information from subjects; the rest are wage-risk studies, which base WTP estimates on estimates of the additional compensation demanded in the labor market for riskier jobs. Because this VSL-based unit value does not distinguish among people based on the age at their death or the quality of their lives, it can be applied to all deaths. Table 22 presents the central unit value from the 26 value of statistical life studies and their underlying distribution.

Table 22. Central Unit Value for VSL based on 26-value-of-life studies

Basis for Estimate	Age Range at Death		Unit Value (VSL) (2015\$)	Distribution of Unit Value	Parameters of Distribution	
	Min	Max			P1	P2
VSL, based on 26 value of statistical life studies	0	99	8,705,114	Weibull	9,648,168	1.509588

## 5.2 HOSPITALIZATIONS AND EMERGENCY DEPARTMENT VISITS

To value hospitalizations, emergency room visits we develop primary COI estimates using data from the Healthcare Cost and Utilization Project (HCUP). The 2016 National Inpatient Sample (NIS) and Nationwide Emergency Department Sample (NEDS) provide recent, nationally representative information on medical treatment in hospitals and emergency departments. In the case of hospital admissions, valuation estimates are calculated as a combination of medical costs and the opportunity cost of time spent at the hospital, measured by lost wages during the hospital stay. In the case of



emergency department visits, valuation estimates include only the medical costs. These cost components are summarized in Table 23.

Table 23. Hospitalization and Emergency Department Cost Elements by Endpoint

Endpoint	Medical Costs (Emergency Room)	Medical Costs (Hospital)	Lost Productivity
Hospitalizations		✓	✓
Emergency department visits	✓		
Emergency hospitalizations	✓	✓	✓

The NIS and NEDS datasets include discharge-level observations. That is, each data point represents one individual being discharged from the hospital (NIS) or emergency department (NEDS). Because individuals are treated in these settings for a variety of reasons, we use medical billing codes to extract observations related to each health endpoint. The epidemiological studies described above provide ICD-9 codes for each illness; however, recent HCUP datasets (including NIS and NEDS) use ICD-10 codes. Thus, we first crosswalk the relevant ICD-9 codes to associated ICD-10 codes using a mapping provided by the U.S. Centers for Disease Control.<sup>67</sup> We then identify all discharges in the HCUP datasets with ICD-10 codes that match to a study’s ICD-9 code(s).<sup>68</sup> Because HCUP datasets often include multiple ICD-10 codes for each discharge, we focus on the principal diagnosis (i.e., the first-listed ICD-10 code). Other key variables used from HCUP include total charges, cost-to-charge ratio (NIS), and length of stay (NIS).

In the NIS dataset, we convert total charges (i.e., the amount billed to patients, employers, or insurance providers) into estimates of total costs (i.e., the final reimbursements for medical treatment). Unadjusted charges are not suitable for use in regulatory analysis because posted prices generally do not reflect actual medical costs due, in part, to negotiation between medical providers and payers (e.g., insurance companies). We assume that adjusted charges reflect the actual revenue the hospital receives and thus the actual cost of providing care. This conversion is completed using hospital-specific cost-to-charge (CCR) ratios provided with NIS. Because CCRs are not available for NEDS, we apply average CCRs for each endpoint in NIS to the same set of ICD-10 codes in NEDS.

For each health endpoint, mean estimates are calculated using estimation commands for survey data to account for the sampling design and sample discharge weights of the HCUP data. This results in estimates of mean costs and a 95% confidence interval, which represents uncertainty in our valuation estimates of medical costs. The resulting estimates are presented in Table 24. Confidence intervals for length of stay cannot be accounted for in the valuation methodology because the EPA’s current tool is only capable of reflecting uncertainty in one parameter.

<sup>67</sup> General Equivalence Mapping Files, FY 2016 release of ICD-10-CM. <https://www.cdc.gov/nchs/icd/icd10cm.htm>.

<sup>68</sup> For emergency hospitalizations, we further restrict the sample to (1) hospitalizations designated as “emergency” and (2) emergency department visits that result in hospitalization.

Table 24. Medical Costs and Hospital Stay Data

Endpoint	Studies	ICD Codes	Age Range		Mean Hospital Charge (2015\$)	Mean Length of Stay (days)	Total Cost of Illness (Unit Value in 2015\$)*
			Start	End			
HA, All Cardiac Outcomes	(Talbot, Rager et al. 2014)	390-459	0	99	\$16,045	5.05	\$16,918
HA, All Respiratory	(Ostro, Roth et al. 2009)	460-519	0	18	\$9,075	3.49	\$9,678
HA, Alzheimer's Disease	(Kioumourtzoglou, Schwartz et al. 2016)	331.0**	65	99	\$10,696	7.95	\$12,070
HA, Cardio-, Cerebro- and Peripheral Vascular Disease	(Bell, Son et al. 2015)	410- 414, 429, 426-427, 428, 430-438, 440-449	65	99	\$14,665	4.82	\$15,498
HA, Respiratory-1	(Jones, Diez-Roux et al. 2015)	491, 492, 493, 496	0	99	\$7,676	3.86	\$8,343
HA, Respiratory-2	(Bell, Son et al. 2015)	464-466, 480-487, 490-492, 493	65	99	\$9,003	4.66	\$9,808
HA, Ischemic Stroke (ICD9 433.X1, 434.X1, 436)	(Danesh Yazdi, Wang et al. 2021)	433.X1, 434.X1, 436**	65	99	\$12,212	4.29	\$12,954
HA, Atrial Fibrillation and Flutter (ICD9 427.3)	(Danesh Yazdi, Wang et al. 2021)	427.3**	65	99	\$10,656	3.66	\$11,288
HA, Parkinson's Disease	(Kioumourtzoglou, Schwartz et al. 2016)	332	18	99	\$12,190	3.83	\$12,852

\* The opportunity cost of a day spent in the hospital was estimated, for the above exhibit, at the median daily wage of all workers, regardless of age. The median daily wage was calculated by dividing the median weekly wage (\$864 in 2015\$) by 5. The median weekly wages for 2015 were obtained from the U.S. Census Bureau's 2015 American Community Survey, "Selected Economic Characteristics: 2015 American Community Survey 1-Year Estimates."

\*\*Although the health impact function and incidence data were developed using the 331.0 ICD-9 code for Alzheimer's Disease, the COI was derived using the three-digit ICD-9 code of 331. Therefore, the COI is representative of all health endpoints captured by the 331 ICD-9 code.

### 5.3 HEALTH ENDPOINT ONSET/OCCURRENCE

Monetary valuation estimates for health endpoint onset or occurrences are described below, listed in alphabetical order. Onset indicates the development of a health endpoint (e.g., asthma diagnosis), whereas occurrence refers to an instance of that health endpoint (e.g., asthma attack).

#### 5.3.1 Acute Myocardial Infarctions (AMIs)

Economic values for acute myocardial infarctions (AMIs, also known as heart attacks) have been updated to be derived from (O'Sullivan, Rubin et al. 2011), which estimate three-year medical costs associated with cardiovascular disease events among adults ages 35 and older in the U.S. The authors rely on administrative claims data from a large U.S. health plan and develop econometric models to estimate medical costs for 15 different cardiovascular events, including AMIs. The dataset includes over 20 million commercial and Medical Advantage members between 2002 and 2006. AMIs are identified using the ICD-9 code 410. The authors use propensity score matching to develop a control group with which to compare costs versus individuals that suffered AMIs. We exclude medical costs within the month of the event in an attempt avoid double counting hospitalization costs, which are captured separately in the hospitalization valuation endpoints. Over three years, the total medical costs, excluding hospitalization, are \$49,758 (undiscounted, inflated to 2015\$), or \$49,108 using a 2% discount rate. (Table 25). Although this study analyzed costs associated with individuals ages 35 and older, we apply the total medical costs to all ages from zero to 99 since only a small portion (<10%) of annual AMI incidence occurs in the age range below 35.

Table 25. Medical Costs for AMIs (2015\$)

Costs	Cumulative Costs	Annual Costs	
		Undiscounted	2% Discount Rate
<i>Month of Event*</i>	\$43,523	\$43,523	\$43,523
Year 1	\$70,629	\$27,106	\$27,106
Year 2	\$82,591	\$11,962	\$11,727
Year 3	\$93,281	\$10,690	\$10,275
<b>Years 1-3</b>	\$93,281	\$49,758	\$49,108

We supplement AMI medical costs with estimates of lost earnings using age-specific estimates from (Cropper and Krupnick 1990). Using a 2% discount rate, we estimated the following present discounted values in lost earnings over 5 years due to a heart attack: 0.229 times annual earnings for someone between the ages of 25 and 44, 0.371 times annual earnings for someone between the ages of 45 and 54, and 1.306 times annual earnings for someone between the ages of 55 and 65. (Cropper and Krupnick 1990) does not provide lost earnings estimates for populations under 25 or over 65. As such we do not include lost earnings in the cost estimates for these age groups. These costs, along with the total valuation estimates for AMIs, are presented in Table 26.

Table 26. Total Valuation Estimates for AMIs (2015\$)

Age Range		Medical Cost	Lost Earnings Multiplier	Total Cost
Min	Max			
0	24	\$49,108	0	\$49,108
25	44	\$49,108	0.219	\$49,108 + 0.219*earnings
45	54	\$49,108	3.534	\$49,108 + 3.534*earnings
55	65	\$49,108	1.245	\$49,108 + 1.245*earnings
66	99	\$49,108	0	\$49,108

### 5.3.2 Allergic Rhinitis (Hay Fever)

Two potential valuation sources for allergic rhinitis were reviewed: (Soni 2008) and (Bhattacharyya 2011). Both studies utilize data from the Medical Expenditure Panel Survey (MEPS) and identify allergic rhinitis (also referred to as hay fever) using ICD-9 code 477. Each study analyzes medical expenditures for differing years, (Soni 2008) for the years 2000 and 2005, and (Bhattacharyya 2011) for the year 2007. (Soni 2008) calculates the cost-of-illness for allergic rhinitis as the mean expenditures for ambulatory care, in-patient services, and prescription medications per person. (Bhattacharyya 2011) calculates the incremental difference in annual healthcare expenditures for individuals with and without allergic rhinitis. Although (Bhattacharyya 2011) uses more recent data, the estimates are not specific to children. Therefore, we derived our COI estimates from the 2005 data presented by (Soni 2008), which are stratified by age group. The resulting COI for allergic rhinitis is \$600 for ages zero to seventeen (2015\$; Table 21). These COI estimates represent mean annual medical costs for patients with hay fever. Given that the health impact function for this endpoint relates to allergic rhinitis prevalence, these estimates are more applicable than values representing only first-year costs.

### 5.3.3 Asthma Onset

Maniloff and Fann (2023) estimated the lifetime costs of asthma using data from the 2017 to 2019 Medical Expenditure Panel Survey (MEPS). The paper identifies individuals with asthma based on individual surveys. Average annual health care costs, lost wages, and caregiving costs are estimated using a regression approach. These were estimated to be \$3267, 2988, and 109, respectively, for a total cost of \$6361. The present value is calculated by summing the discounted average annual costs over the average lifespan. Health care costs are updated based on the health care cost index, while wage and caregiving costs are updated based on wage indices. The MEPS primarily includes respondents 18 years or older.

### 5.3.4 Asthma Symptoms/Exacerbation

#### 5.3.4.1 Albuterol Use

As albuterol use is a new measure of PM<sub>2.5</sub>-attributable asthma symptoms, we developed a method for valuing this health endpoint. We estimate the economic value for albuterol use associated with asthma symptoms using prescription prices for albuterol inhalers. Epocrates and GoodRx provide cost and actuation information for four common types of albuterol inhalers in 2020 dollars.<sup>70,71</sup> Both online

<sup>70</sup> <https://online.epocrates.com/drugs> searched March 19th, 2020.

<sup>71</sup> <https://www.goodrx.com/albuterol> searched March 19th, 2020.

resources utilize published price lists, purchases, claim records, and pharmaceutical data to provide clinical statistics. Epocrates and the FDA provide cost and actuation information for one additional, less common, albuterol inhaler.<sup>72</sup> We divide the cost of inhalers by the actuations per inhaler to calculate an average cost per actuation across all inhaler types. We then adjust the values to 2015\$ using the Consumer Price Index (CPI) for medical care. Since medical cost index data were unavailable for 2020 at the time of these calculations, we used the most recently available index (2019). The resulting value for asthma symptoms, albuterol use is \$0.35 per actuation (2015\$) (Table 21).

#### *5.3.4.2 Cough, Wheeze, Chest Tightness, and Shortness of Breath*

While the risk estimates for both PM<sub>2.5</sub>- and O<sub>3</sub>-attributable asthma symptoms were updated, the valuation estimates for cough, wheeze, chest tightness, and shortness of breath are still based on the previous method, using the (Dickie and Messman 2004) analysis of parents' WTP to relieve asthma symptoms in children and adults. The authors derive the WTP estimates from an attribute-based, stated-choice question assessing preferences to avoid acute illness as part of a survey performed in Hattiesburg, Mississippi in 2000. Survey respondents are asked to identify whether they or their child have experienced the following asthma symptoms in the past year: cough with phlegm, shortness of breath with wheezing, chest pain on deep inspiration, and fever with muscle pain and fatigue. Respondents were then assigned one of sixteen illness profiles varying by symptom, symptom duration, in days, as well as discomfort level. (Dickie and Messman 2004) calculate the WTP for children ages zero to seventeen as \$219, for one avoided mild symptom-day (2015\$). The authors also provide WTP estimates by symptom, however, they represent six avoided symptom-days. Therefore, we apply the same WTP value, for one avoided mild symptom-day, to each asthma symptom endpoint (Table 21).

#### **5.3.5 Cardiac Arrest**

The COI for cardiac arrests occurring outside of the hospital is derived from (O'Sullivan, Rubin et al. 2011), who estimate three-year medical costs associated with cardiovascular disease events among adults ages 35 and older in the U.S. The authors rely on administrative claims data from a large U.S. health plan and develop econometric models to predict medical costs for 15 different cardiovascular events, including cardiac arrest, referred to as resuscitated cardiac arrest. The dataset includes over 20 million commercial and Medical Advantage members between 2002 and 2006. Cardiac arrests are identified using the ICD-9 code 427.5. The authors use propensity score matching to develop a control group with which to compare costs versus individuals that suffered cardiac arrest. Medical costs occurring within the month of the event were excluded to avoid double counting hospitalization costs, which are separately captured by the hospitalization valuation functions. Over three years, the total medical costs, excluding hospitalization, are \$36,142 (undiscounted, inflated to 2015\$), or \$35,880 using a 2% discount rate (Table 27 and Table 21).

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<sup>72</sup> [https://www.accessdata.fda.gov/drugsatfda\\_docs/label/2016/205636s006lbl.pdf](https://www.accessdata.fda.gov/drugsatfda_docs/label/2016/205636s006lbl.pdf)

Table 27. Valuation Estimate for Cardiac Arrests (2015\$)

Costs	Cumulative Costs	Annual Costs	
		Undiscounted	2% Discount Rate
<i>Month of Event*</i>	\$43,904	\$43,904	\$43,904
Year 1	\$71,901	\$27,997	\$27,997
Year 2	\$74,701	\$2,800	\$2,745
Year 3	\$80,046	\$5,345	\$5,137
<b>Years 1-3</b>	\$80,046	\$36,142	\$35,880

### 5.3.6 Lung Cancer

The unit value for non-fatal lung cancer incidence is derived from the direct medical costs of lung cancer treatment estimated by (Kaye, Min et al. 2018). This COI value incorporates only direct medical costs and not lost earnings associated with lung cancer incidence because the average age of lung cancer diagnosis is approximately 70 and it is assumed that those aged 65 and older are retired and thus have exited the labor market. Lung cancer treatment costs depend to a large extent on the phase of care, with costs in the initial year of treatment (e.g., \$17,422 for males) far exceeding the continuing costs of treatment in subsequent years (e.g., \$3,269 for males). We calculate costs over a five-year span, beginning with the initial onset which occurs with a delay after exposure. The specific lag periods between exposure and onset are discussed in Section 6.4.2. The initial year's treatment cost is summed with four years of continuing annual costs discounted at 2%.

Furthermore, (Kaye, Min et al. 2018) provides separate treatment cost estimates for men and women. The distribution of new lung cancer cases by sex in the United States from (Siegel, Miller et al. 2019) is approximately 51% male and 49% female. This distribution of new lung cancer cases was used to weight the sex-specific cost estimates from (Kaye, Min et al. 2018) to obtain a combined five-year cost estimate for both sexes. In order to adjust the cost estimate to 2015\$ using a medical cost index, we assume that costs presented by (Kaye, Min et al. 2018) are in 2010\$ as an approximate midpoint of the data years 2007-2012. Altogether, the cost of non-fatal lung cancer incidence over a five-year period is estimated to be \$34,155 using a 2% discount rate. (Table 21).

For an outcome such as lung cancer, there is an expected time lag between changes in pollutant exposure in a given year and the total realization of health effect benefits, commonly referred to in regulatory analyses as the "cessation lag." The time between exposure and diagnosis can be quite long, on the order of years to decades, to realize the full benefits of the air quality improvements. This latency period is important in order to properly discount the economic value of these health benefits.

To estimate the latency period, we performed a literature search using the keywords "non-fatal lung cancer," "lung cancer," "PM<sub>2.5</sub>," "latency," and "incidence." Five papers that estimate the risk of lung cancer incidence from PM<sub>2.5</sub> exposure using a latency period were identified. The latency period length and country of the identified papers are summarized in Table 28. Based on estimates of lung cancer latency from the literature, 10 years was the most common latency period estimate found in the literature (i.e., the mode).

Table 28. Latency Periods Used in Lung Cancer Risk Assessment Papers

Study	Latency Period (years)	Location
(Gogna, Narain et al. 2019)	5	Canada
(Bai, Shin et al. 2020)	4; 10	Canada
(Kulhanova, Morelli et al. 2018)	10	France
(Coleman, Burnett et al. 2020)	10; 15	US
(Harrison, Smith et al. 2004)	20	US

To account for the latency period between air pollution reductions and avoided lung cancer diagnoses in our economic valuation estimates, we developed an age-at-diagnosis cessation lag distribution method based on an approach previously used to estimate avoided cases of kidney cancer in analyses of water quality rules ((U.S. EPA 2017)). The method uses lung and bronchus cancer diagnosis age-distribution from the Surveillance, Epidemiology, and End Results Program (SEER). For this model, we assumed that the case reduction distribution would follow the age-pattern of cancer diagnosis between the age at which the exposure change occurs and 99 years. Table 29 shows an example case reduction distribution calculation for an exposure change experienced at 55. SEER estimates 92.2% of lung and bronchus cancer cases occur in individuals 55 years and older. Dividing the percentages in the remaining age bins by 92.2% (the percent of lung and bronchus cancer diagnoses between the age of exposure change and end of lifetime), we find that there is a 24% chance that the risk reductions for a 55-year-old occur between ages 55 and 64, a 37% chance that the case reductions occur between ages 65 and 74, etc. For distributing avoided cases within an age bin, we assume an equal incidence distribution across years within each bin.

Table 29. Percent Lung and Bronchus Cancer Incidence by Age and Distribution of Risk Reduction by Age for an Exposure Change at 55

Age Group	Percent New Cases per Year by Age*	Percent of New Cases Occurring at or After Age 55 <sup>1</sup>
0-20	0	NA
20-34	0.2	NA
35-44	0.9	NA
45-54	6.6	NA
55-64	21.8	24
65-74	34.1	37
75-84	26.6	29
85-99	9.7	11
55-99	92.2	100

\*May not sum to 100% due to rounding

<sup>1</sup>Calculated as the percentage in column 2 divided by 92.2%, where 92.2% is the percentage of lung and bronchus incidence between age 55 and 99.

This and other potential cessation lag distribution models for lung cancer onset are described and compared in section 6.4.2.

### 5.3.7 Minor Restricted Activity Days (MRADs)

Due to their definition, for the purposes of benefits estimation minor respiratory-restricted activity days (MRRAD) are assumed to constitute all MRADs ((Ostro and Rothschild 1989)). While no peer-reviewed studies estimating WTP to avoid a MRRAD are available, a central estimate and upper and lower bounds of WTP to avoid a MRRAD were developed by IEc ((IEc 1993)).<sup>73</sup> When estimating benefits associated with an MRAD, we use a triangular distribution centered at the estimate.

Any estimate of mean WTP to avoid a MRRAD (or any other type of restricted activity day other than Work Loss Day (WLD)) will be somewhat arbitrary because the endpoint itself is not precisely defined. Many different combinations of symptoms could presumably result in some minor or less minor restriction in activity. (Krupnick and Cropper 1992) argued that mild symptoms will not be sufficient to result in a MRRAD, so that WTP to avoid a MRRAD should exceed WTP to avoid any single mild symptom. A single severe symptom or a combination of symptoms could, however, be sufficient to restrict activity. Therefore, WTP to avoid a MRRAD should, these authors argue, not necessarily exceed WTP to avoid a single severe symptom or a combination of symptoms. The “severity” of a symptom, however, is similarly not precisely defined; moreover, one level of severity of a symptom could induce restriction of activity for one individual while not doing so for another. The same is true for any combination of symptoms.

Given that there is inherently a substantial degree of arbitrariness in any point estimate of WTP to avoid a MRRAD (or other kinds of restricted activity days), the reasonable bounds on such an estimate must be considered. By definition, a MRRAD does not result in loss of work. WTP to avoid a MRRAD should therefore be less than WTP to avoid a WLD. At the other extreme, WTP to avoid a MRRAD should exceed WTP to avoid a single mild symptom. The highest IEc midrange estimate of WTP to avoid a single symptom is \$28.51 (2015\$), for eye irritation. The point estimate of WTP to avoid a WLD in the benefit analysis is \$110.62 (2015\$). If all the single symptoms evaluated by the studies are not severe, then the estimate of WTP to avoid a MRRAD should be somewhere between \$28.51 and \$110.62. Because the IEc estimate of \$69.58 (2015\$) falls within this range (and acknowledging the degree of arbitrariness associated with any estimate within this range), we use the IEc estimate of \$69.58 (2015\$) (Table 21).

### 5.3.8 School Loss Days

We include two costs of school loss days: caregiver costs and loss of learning. We calculate each separately and then sum them. Caregiver costs are valued at their employers’ average cost for employed caregivers. For unemployed caregivers, the opportunity cost of their time is calculated as the average take-home pay. The loss of learning is calculated based on the impact of absences on learning multiplied

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<sup>73</sup> IEc (1993). Memorandum to Jim DeMocker, U.S. Environmental Protection Agency, Office of Air and Radiation, Office of Policy Analysis and Review. September 30., U.S. EPA. derived this estimate of WTP to avoid a MRRAD using WTP estimates from Tolley, G. S., L. Babcock, M. Berger, A. Bilotti, G. Blomquist, M. Brien, R. Fabian, G. Fishelson, C. Kahn and A. Kelly (1986). Valuation of reductions in human health symptoms and risks. Prepared for US Environmental Protection Agency, U.S EPA. for avoiding a three-symptom combination of coughing, throat congestion, and sinusitis. This estimate of WTP to avoid a MRRAD, so defined, is \$69.58 in 2015\$.



by the impact of school learning on adult earnings. The loss of learning estimate is currently only available for middle and high school students. The two costs are summed.

The caregiver costs assumes that an adult caregiver stays home with the child and loses any wage income they would have earned that day. For working caregivers, we follow U.S. EPA guidance and value their time at the average wage including fringe benefits and overhead costs (U.S. EPA, 2020a). We apply a multiplier of 1.46 for fringe benefits based on the U.S. Bureau of Labor Statistics' 2023 National Compensation Survey and 1.2 for overhead from U.S. EPA's National Center for Environmental Economics (NCEE) to county-specific mean wage estimates from the 2021 5-year American Community Survey (ACS). For nonworking caregivers, we assume that the opportunity cost of time is the average after tax earnings. We estimate the income tax rate for a median household to be 7% and apply to 2021 ACS county-specific mean wage estimates. The income tax rate of 7% is the percentage difference in median post-tax income and median income from (U.S. Census Bureau, 2021). We then apply county-specific employment-population ratios from the 2021 ACS to yield county-specific estimates of caregiver costs per school loss day. The average of this county-specific measure across all counties is approximately \$235 (2015\$).

To measure the loss of learning, we update the Liu et al., 2021 estimate of the impact of a school absence on learning as measured by an end-of-course test score. Liu et al., 2021 provide an estimate that a school absence leads to a \$1,200 reduction in lifetime earnings, which is based on the Chetty et al., 2014 estimate of mean lifetime earnings (\$522,000 in 2010\$). We first use 2015 Current Population Survey data from the U.S. Census to calculate expected lifetime earnings of \$1,137,732 (discounting at 2%). We then multiply the Liu et al., 2021 estimate of \$1,200 by  $(1,137,732/522,000)$  and convert from 2010 dollars to 2015 dollars based on the Consumer Price Index for All Urban Consumers. This approach yields an estimated learning loss of \$2,843 per school absence (discounted at 2%).

For BenMAP application, we create a valuation function that uses caregiver costs for preschool and elementary school children and the sum of caregiver costs and loss of learning for middle school and high school students. We calculate that 31% of children under 18 are middle school and high school ages 13-18, distributed equally across the two bins); thus, we estimate county-specific averages of the combined effect by summing the county-specific estimates of caregiver costs and  $(\$2,843*0.31)$  with 2% discounting. The average of this county-specific measure across all counties is approximately \$1,116 (discounted at 2%) per school day for ages 0 to 17 (2015\$).

A unit value based on the approach described above is likely to understate the value of a school loss day in at least four ways:

- 1) It omits WTP to avoid the symptoms/illness which resulted in the school absence
- 2) The approach omits other aspects of school attendance such as social and emotional development or meals
- 3) It does not account for deleterious effects on student learning which are not captured by a single end-of-grade test score. These other effects might include lost learning in other subjects such as science, language arts, and history, as well as social and emotional development.

### 5.3.9 Stroke

Maniloff and Fann (2023) developed COI estimates of direct and delayed health care costs, loss of wage income, and home paid caregiving costs associated with a non-fatal first stroke. The authors conduct a regression analysis based on 2017 – 2019 medical expenditure data from the Agency for Healthcare Research and Quality’s (AHRQ’s) Medical Expenditure Panel Survey (MEPS) to estimate the difference in total medical expenditures between individuals who report having been diagnosed with new onset stroke and otherwise similar individuals who do report a stroke diagnosis. This approach allows for inclusion of direct medical costs due to the stroke itself and medical costs due subsequent health effects that may be related to having experienced a stroke (sequelae). The MEPS data includes actual (not billed) insurer payments, government payments and individual payments, and includes agency and non-agency paid caregiving<sup>15</sup> in its caregiving cost estimates. The authors report the annual costs and present value of lifetime costs of a first stroke for those ages 18 and older, broken into three cost categories: health care, lost wage income, and home caregiving. The authors estimated lifetime costs using data on expected remaining life expectancy at age of first stroke; the resulting present value lifetime estimates are the values used in the BenMAP valuation function. The study estimated the average present value lifetime COI for a new onset stroke to be \$159,067 (2015\$) using a 2% discount rate.

### 5.3.10 Work Loss Days (WLDs)

Work loss days are valued at a day’s wage. BenMAP calculates county-specific mean daily wages from county-specific annual wages by dividing by (52\*5), then applies a multiplier of 1.46 for fringe benefits estimates based on the U.S. Bureau of Labor Statistics’ 2023 National Compensation Survey and an overhead multiplier of 1.2 from U.S. EPA’s National Center for Environmental Economics (NCEE) as described in U.S. EPA (2014) for workers as defined by county-specific employment rate data from the 5-year 2021 American Community Survey. The average of this county-specific daily wage measure across all counties is approximately \$298 for ages 18 to 65 (2015\$) (Table 21).

## 5.4 DEVELOPING INCOME GROWTH ADJUSTMENT FACTORS FOR HEALTH ENDPOINT ONSET/OCCURRENCE

Chapter 4 of the BenMAP-CE User Manual provides instructions for formatting and adding income growth data ((U.S. EPA 2018)). These values are used to adjust WTP estimates for growth in real income. As discussed in that chapter, evidence and theory suggest that WTP should increase as real income increases. When reviewing the economic literature to develop income growth adjustment factors, it is important to have an economist assist. For an overview of valuation, see Chapter 7 of the BenMAP-CE User Manual, “Aggregating, Pooling, and Valuing”.

Adjusting WTP to reflect growth in real income requires three steps:

1. *Identify relevant income elasticity estimates from the peer-reviewed literature.*
2. *Calculate changes in future income.*
3. *Calculate adjustments to WTP based on changes in future income and income elasticity estimates.*

### 1. Identifying income elasticity estimates

Income elasticity estimates relate changes in demand for goods to changes in income. Positive income elasticity suggests that as income rises, demand for the good also rises. Negative income elasticity suggests that as income rises, demand for the good falls. We do not adjust COI estimates according to changes in income elasticity due to the fact that COI estimates the direct cost of a health outcome; instead, we adjust this metric using inflation factors described above. We include income elasticity estimates specific to the type of health endpoint associated with the WTP estimate for three types of health effects: minor, severe and mortality. Minor health effects are those of short duration. Severe, or chronic, health effects are of longer duration. Consistent with economic theory, the peer reviewed literature indicates that income elasticity varies according to the severity of the health effect. A review of the literature revealed a range of income elasticity estimates that varied across the studies and according to the severity of health effect. Table 30 summarizes the income elasticity estimates for minor health effect, severe health effect and mortality. Here we have provided a lower, upper, and central elasticity estimate for each type of health endpoint.

Table 30. Income Elasticity Estimates for Minor Health Effects, Severe Health Effects, and Mortality

<b>Health Endpoint</b>	<b>Lower Bound</b>	<b>Central Estimate</b>	<b>Upper Bound</b>
Minor Health Effect	0.04	0.15	0.30
Severe and Chronic Health Effects	0.25	0.45	0.60
Mortality	0.08	0.40	1.00

## 2. Calculating changes in future income

The next input to the WTP adjustment is annual changes in future income. The Congressional Budget Office’s ten-year projections of US Gross Domestic Product (GDP) are used to estimate changes in future income ((CBO 2016)). Historical GDP data came from the U.S. Bureau of Commerce’s Bureau of Economic Analysis. GDP values were adjusted for inflation as needed using the Implicit Price Deflator annual index, published by the Economic Research Division of the Federal Reserve Bank of St. Louis. We divided the projected change in GDP by the (Woods & Poole 2015) projected change in total US population to produce an estimate of the future GDP per capita.

## 3. Calculating changes in WTP

The income elasticity estimates from Table 30 and the estimated changes in future income may then be used to estimate changes in future WTP for each health endpoint. The adjustment formula follows four steps:

$$1) \quad \varepsilon = \frac{\frac{\Delta WTP}{WTP}}{\frac{\Delta I}{I}} = \frac{(WTP_2 - WTP_1) \times (I_2 + I_1)}{(I_2 - I_1) \times (WTP_2 + WTP_1)}$$

$$2) \quad \varepsilon I_2 WTP_2 + \varepsilon I_2 WTP_1 - \varepsilon I_1 WTP_2 - \varepsilon I_1 WTP_1 = I_2 WTP_2 + I_1 WTP_2 - I_2 WTP_1 - I_1 WTP_1$$

$$3) \quad WTP_2 \times (\varepsilon I_2 - \varepsilon I_1 - I_2 - I_1) = WTP_1 \times (\varepsilon I_1 - \varepsilon I_2 - I_1 - I_2)$$

$$4) \quad WTP_2 = WTP_1 \times \frac{\varepsilon I_1 - \varepsilon I_2 - I_1 - I_2}{\varepsilon I_2 - \varepsilon I_1 - I_2 - I_1}$$

Table 31 summarizes the income-based WTP adjustments used within BenMAP-CE for minor health endpoints, severe health endpoints, and premature mortality. BenMAP-CE applies the “mid” income growth adjustment to the WTP for each corresponding health endpoint. The “low” and “upper” are provided for bounding the “mid” estimate. More information on the uncertainties associated with the choice of income elasticity is provided in section 6.4.3.

Table 31. Income-Based WTP Adjustments by Health Effect and Year

Year	Minor Health Endpoint			Severe Health Endpoint			Mortality		
	Low	Mid	Upper	Low	Mid	Upper	Low	Mid	Upper
1990									
1991	0.99943614	0.997887194	0.995778859	0.99648118	0.993674994	0.991575539	0.998872638	0.994375765	0.985998511
1992	1.00027895	1.0010463	1.002093554	1.00174439	1.003141999	1.004191637	1.000557899	1.002792478	1.006995797
1993	1.00083518	1.003135324	1.006280541	1.005231023	1.009435654	1.01260066	1.001670957	1.008382797	1.021089673
1994	1.001928926	1.007252812	1.014558434	1.012117267	1.021917462	1.029330373	1.003861666	1.019458413	1.049366593
1995	1.00252676	1.009508491	1.019107819	1.01589787	1.028799176	1.038584113	1.005059958	1.025558352	1.065144777
1996	1.003553152	1.013389945	1.026960373	1.022416711	1.040715098	1.054657698	1.00711906	1.036109447	1.092786551
1997	1.004830718	1.018236518	1.036808729	1.030580044	1.055725813	1.074997663	1.00968492	1.049381137	1.128201008
1998	1.006105304	1.023088813	1.046717048	1.038779855	1.070903659	1.095668674	1.012248039	1.062778115	1.164700031
1999	1.007476926	1.028329492	1.057473063	1.047665954	1.087466359	1.118347049	1.01500988	1.077371955	1.205345869
2000	1.008633733	1.032765627	1.066622734	1.055212379	1.101626635	1.137836933	1.017342448	1.089827657	1.24079144
2001	1.008626103	1.032736301	1.066562176	1.05516243	1.101532698	1.137707233	1.01732707	1.089745045	1.240554214
2002	1.008962274	1.034028053	1.069233894	1.057363987	1.105680108	1.143433094	1.018005252	1.093389511	1.251058578
2003	1.009722471	1.036953092	1.075297475	1.062356591	1.115113139	1.156486392	1.019539833	1.10167253	1.275163889
2004	1.010831594	1.041232586	1.084201217	1.069678664	1.129017591	1.175803781	1.021781206	1.11386621	1.31124568
2005	1.011770725	1.044866562	1.091792464	1.075912952	1.140922546	1.192415953	1.023680925	1.12429142	1.342671752
2006	1.012430668	1.047425628	1.097154975	1.080312252	1.149360299	1.204231024	1.025016785	1.131672144	1.36525023
2007	1.01275146	1.048671246	1.099770427	1.08245647	1.153483868	1.210017681	1.025666475	1.135276675	1.376378059
2008	1.012262344	1.04677248	1.095784903	1.079188704	1.147202373	1.201206207	1.024675965	1.12978518	1.359451532
2009	1.01079917	1.041107416	1.083940148	1.069464207	1.12860918	1.175235033	1.021715641	1.113508224	1.310176253
2010	1.011459589	1.043661356	1.089271665	1.073843718	1.136964202	1.186884999	1.023051262	1.120826483	1.332167268
2011	1.011786222	1.044926405	1.091917515	1.076015592	1.141119123	1.192690849	1.023712158	1.124463439	1.343194842
2012	1.012354255	1.047128916	1.096532583	1.079801798	1.148379683	1.202856183	1.024862051	1.130814672	1.362613082
2013	1.012712717	1.048520923	1.099454761	1.082197666	1.15298593	1.209318399	1.025588155	1.134841442	1.375030875
2014	1.013344169	1.050976157	1.104618788	1.086428881	1.161142945	1.220786929	1.026867747	1.141967177	1.397211194
2015	1.014022827	1.053619623	1.110193372	1.090992332	1.169972539	1.233237505	1.02824378	1.149673343	1.421498775
2016	1.014274955	1.054602981	1.11227107	1.092692018	1.173269868	1.237896562	1.028755188	1.152549148	1.430643797
2017	1.014827728	1.056761265	1.116838455	1.096426606	1.180531025	1.248175263	1.029876947	1.158878565	1.45092845
2018	1.015322924	1.058697701	1.120945096	1.099781871	1.187074065	1.257459402	1.030882478	1.164577603	1.469381213
2019	1.015639186	1.059935808	1.123574972	1.101929545	1.191271544	1.263426423	1.031524897	1.168231487	1.48130703
2020	1.015908599	1.060991406	1.125819683	1.103761792	1.194858909	1.268532872	1.032072306	1.171352863	1.491554141
2021	1.016283393	1.062461257	1.128949761	1.106315613	1.199867845	1.275673389	1.032834172	1.175709248	1.505947828
2022	1.016681671	1.064024925	1.132284641	1.109035254	1.205213666	1.283308029	1.03364408	1.180356026	1.521420956
2023	1.017086029	1.065614223	1.135679722	1.11180234	1.210665345	1.291108131	1.034466624	1.185091853	1.53731966
2024	1.017486334	1.067189336	1.139050007	1.114547729	1.216086745	1.298879623	1.035281181	1.189798594	1.553251266
2025	1.017879009	1.068736196	1.142365217	1.117246628	1.221428633	1.306551456	1.036080599	1.194433689	1.56906867
2026	1.018263578	1.070252538	1.145620227	1.119895339	1.226682782	1.314110994	1.036863804	1.198989868	1.584743023

## 6 CHARACTERIZING UNCERTAINTY AND EVALUATING SENSITIVITY TO ALTERNATE ASSUMPTIONS

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Complex analyses such as the one presented in the Regulatory Impact Analysis for the Proposed Reconsideration of the PM NAAQS use many estimated parameters and inputs. The approach for estimating PM<sub>2.5</sub> and O<sub>3</sub> benefits includes health effect risk estimates from epidemiologic studies, population data, population growth estimates, economic data for monetizing benefits, and assumptions regarding the future state of the world (i.e., on-the-books regulations). When the uncertainties from each stage of the analysis are compounded, even small uncertainties can have large effects on the total quantified benefits.

After reviewing the EPA's approach to quantifying benefits, the National Research Council ((National Resources Council 2004)) highlighted the need to conduct rigorous quantitative analyses of uncertainty and to present benefits estimates to decision makers in ways that foster an appropriate appreciation of their inherent uncertainty. Since the publication of these reports, the EPA has continued improving its techniques for characterizing uncertainty in the estimated air pollution-attributable benefits.

In light of these recommendations, we incorporate new quantitative and qualitative characterizations of uncertainty. Where possible, we quantitatively assess uncertainty in each input parameter (for example, we characterize statistical uncertainty by performing Monte Carlo simulations). We invest the time and resources in performing the most comprehensive uncertainty analyses for those input parameters that most greatly influence on the size of the estimated health impacts.<sup>75</sup>

In some cases, this type of quantitative analysis is not possible due to lack of data, so we instead characterize the sensitivity of the results to alternative plausible input parameters. And, for some inputs into the benefits analysis, such as the air quality data, we lack the data to perform either a quantitative uncertainty analysis or sensitivity analysis.

Sections 6.1 and 6.2 quantitatively describe the uncertainty associated with estimated PM<sub>2.5</sub> and O<sub>3</sub>-attributable incidence, respectively. Section 6.3 provides information on the sensitivity to more granular baseline incidence rates. Section 6.4 quantitatively discusses the influence of uncertainty in the economic valuation functions. Lastly, section 6.5 qualitatively discusses the various potential sources of uncertainty, sometimes including sources of uncertainty touched upon quantitatively.

### 6.1 QUANTITATIVE CHARACTERIZATION OF PM<sub>2.5</sub> UNCERTAINTY AND EVALUATING SENSITIVITY TO ALTERNATE PM<sub>2.5</sub> ASSUMPTIONS

Below we describe our approach for characterizing uncertainty in the estimated PM<sub>2.5</sub>-related effects. We start first with the role of Monte Carlo assessment in generating a quantitative distribution of results. We next describe how alternative risk estimates<sup>76</sup> can be useful for assessing the sensitivity of

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<sup>75</sup> Uncertainties that we expect will have the greatest influence on health impacts are 1) those associated with mortality impacts given the severity of the outcome and the associated economic valuation and 2) quantitative and qualitative uncertainty characteristics likely to impact the magnitude of bias most strongly.

<sup>76</sup> Alternate risk estimates are a means to quantitatively understand uncertainties around the main risk estimate. Alternate risk estimates are based on a different set of input parameters, which may come from the same study or

the estimated PM<sub>2.5</sub>-related mortality and morbidity to plausible alternative input parameters; this gives insight to the influence of the functional form of the model or alternative epidemiologic approaches. Quantitative sensitivity analyses using alternative or additional risk estimates are included for the following PM<sub>2.5</sub>-attributable health endpoints: mortality in adults (section 6.1.1), asthma onset in children (section 6.1.3), cardiovascular hospital admissions (section 6.1.4), and respiratory hospital admissions (section 0).

#### 6.1.1 Statistical Uncertainty Around the Risk Estimate (Monte-Carlo Assessment)

For all endpoints analyzed, we use a Monte Carlo simulation in which we sample from the standard error associated with each risk estimate and present the resulting 2.5<sup>th</sup> and 97.5<sup>th</sup> percentile values from this distribution as a 95<sup>th</sup> percentile confidence interval around the estimated health impact and monetized health benefits. Monte Carlo methods are a well-established means of characterizing random sampling error associated with the risk estimates from epidemiological studies. This approach randomly samples from a distribution of incidence and valuation estimates to characterize the effects of uncertainty in those inputs on output variables. The reported standard errors in the epidemiological studies determined the distributions for individual effect estimates for endpoints estimated using a single study. The confidence intervals around the monetized benefits incorporate the epidemiology standard errors as well as the distribution of the valuation function. These confidence intervals do not reflect other sources of uncertainty inherent within the estimates, such as baseline incidence rates, populations exposed, and transferability of the effect estimate to diverse locations. As a result, the reported confidence intervals and range of estimates give an incomplete picture about the overall uncertainty in the benefits estimates.

#### 6.1.2 Adult All-Cause Mortality<sup>77</sup>

Three studies of all-cause, long-term PM<sub>2.5</sub> exposure and mortality were identified as best characterizing U.S. risk in adults, (Turner, Jerrett et al. 2016, Pope III, Lefler et al. 2019, Wu, Braun et al. 2020). Additional information regarding the cohort concentration exposure distributions (section 6.1.2.1) and additional risk estimates potentially providing insight into the effect of various potential sources of uncertainty, such as different exposure estimation techniques (section 6.1.2.2), confounding by O<sub>3</sub> (section 6.1.2.3), statistical regression techniques and methods to control for confounders (section 6.1.2.4), and effect modification by individual risk factors (section 6.1.6).

##### 6.1.2.1 Low Concentration Exposures

Each epidemiological risk estimate is based on a distribution of air quality concentrations experienced by the original cohort population. As such, it is important to consider the relationship between the concentrations from which the mortality estimates are derived and the concentrations at which the estimates are subsequently applied in future policy scenarios in which concentrations are likely to be lower due to decreasing air pollution trends. When estimating health impacts, we are most confident in results estimated using projected air quality concentrations that closely align with those observed in the epidemiological study from which the risk estimate was obtained (i.e., we are less confident applying risk estimates to pollutant concentrations that do not match the original cohort due to changes in air

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different studies. Alternate risk estimates can be used to assess the sensitivity of the risk estimate to alternative assumptions and input parameters, such as modeling choices, populations, or statistical techniques.

<sup>77</sup> As estimates of infant mortality incidence are relatively small, we do not perform quantitative uncertainty analyses for that health endpoint.

pollutant concentrations over time). To address the potential mismatch between projected air quality levels and those in the epidemiologic study, we include air quality information from the original epidemiologic studies where feasible.

Additional information was requested from mortality study authors regarding the ambient concentrations used to estimate exposure of the original cohort.<sup>78</sup> Study authors provided cohort specific PM<sub>2.5</sub> concentration data at varying levels of detail. PM<sub>2.5</sub> concentrations for the three long-term exposure epidemiologic cohort studies examining mortality, ACS CSP-II and Medicare are presented in Figure 12 ((Turner, Jerrett et al. 2016, Di, Wang et al. 2017, Wu, Braun et al. 2020)); the distribution of PM exposure incorporated in the (Pope III, Lefler et al. 2019) study is reflected in the histogram reported below (Figure 13). We also included the distribution of PM<sub>2.5</sub> concentrations from a recent analysis of the CanCHEC cohort in order to compare to some of the lowest reported concentrations in North America ((Crouse, Peters et al. 2015)). Points reflect cohort specific PM<sub>2.5</sub> concentration data, with connecting lines estimating missing data.

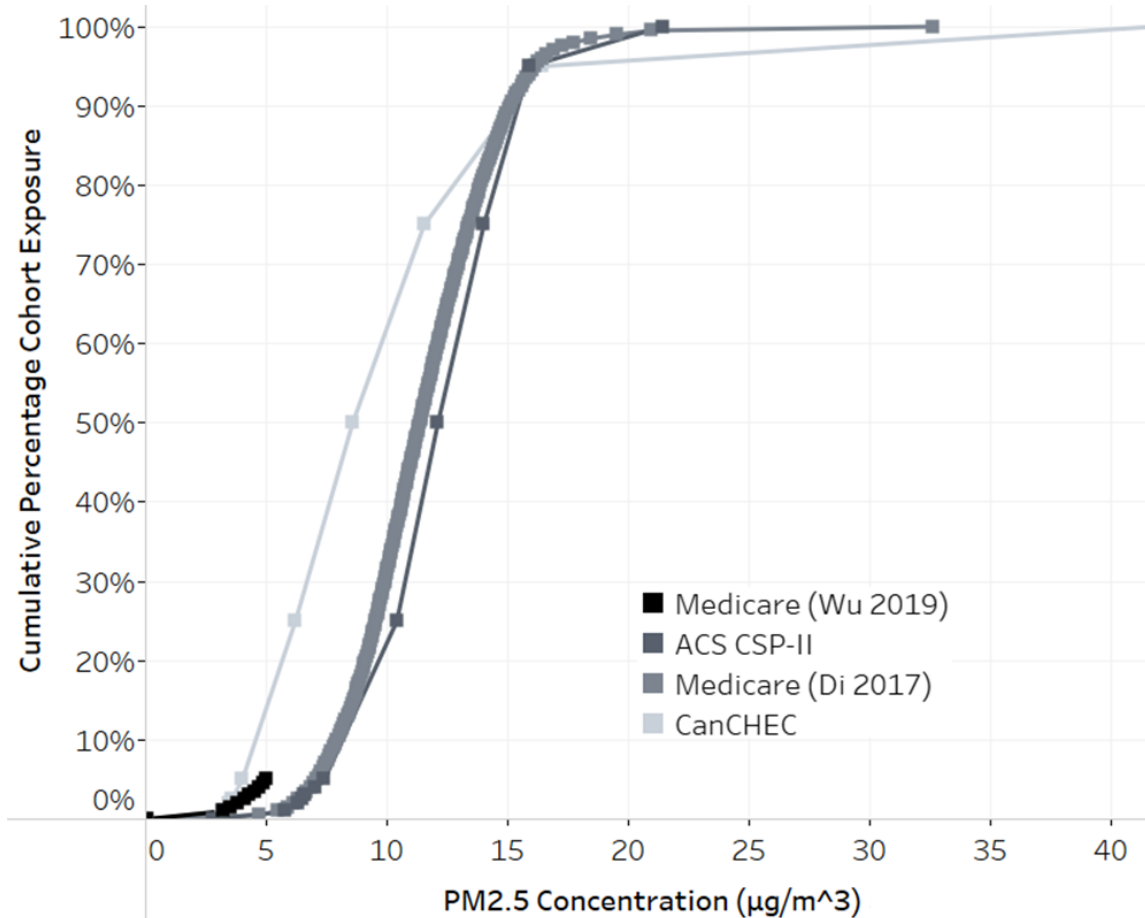


Figure 12. Cumulative Percentile of PM<sub>2.5</sub> Cohort Exposure from the ACS CSP-II, Medicare, and CanCHEC Cohorts

<sup>78</sup> For morbidity studies, author-reported air quality information such as the average or mean, standard deviation, and maximum and minimum concentrations were collected and is available in the corresponding Study Information Table.



As air pollution concentrations continue to decline an increasing fraction of the population will be exposed to PM<sub>2.5</sub> concentrations at the lower end of the air quality distribution experienced by the study cohort. The distribution of PM<sub>2.5</sub> concentrations for each of three large, long-term exposure cohorts are provided in Table 32. For comparison, the lowest reported PM<sub>2.5</sub> concentrations from previous studies ((Krewski, Jerrett et al. 2009, Lepeule, Laden et al. 2012)) in which risk estimates were used to estimate all-cause mortality attributed to long-term PM<sub>2.5</sub> exposure were 5.8 and 8.0 µg/m<sup>3</sup>, whereas the recent studies identified as best characterizing long-term PM<sub>2.5</sub> exposure and the risk of all-cause mortality include PM<sub>2.5</sub> concentrations below 3 µg/m<sup>3</sup> ((Turner, Jerrett et al. 2016, Di, Wang et al. 2017, Pope III, Lefler et al. 2019, Wu, Braun et al. 2020)). Pope and co-authors separately reported the exposure distribution ((Higbee, Lefler et al. 2020)); we report the histogram from this manuscript below.

Table 32. Low Concentration PM<sub>2.5</sub> Exposures from the ACS CSP-II, Medicare, and CanCHEC Cohorts

Cohort	Percentile of Cohort Exposure (µg/m <sup>3</sup> )										
	0.0%	1.0%	1.5%	2.0%	2.5%	3.0%	3.5%	4.0%	4.5%	5.0%	10.0%
ACS CSP-II	2.8	5.8		6.3	6.5	6.6		7.0		7.4	
Medicare	0.0 <sup>A</sup>	3.2	3.5	3.8	4.1	4.3	4.5	4.7	4.9	5.0	6.1
CanCHEC	0.0	3.2		3.5	3.6					4.0	4.7

<sup>A</sup> Lowest modeled value is 0.0078 µg/m<sup>3</sup>

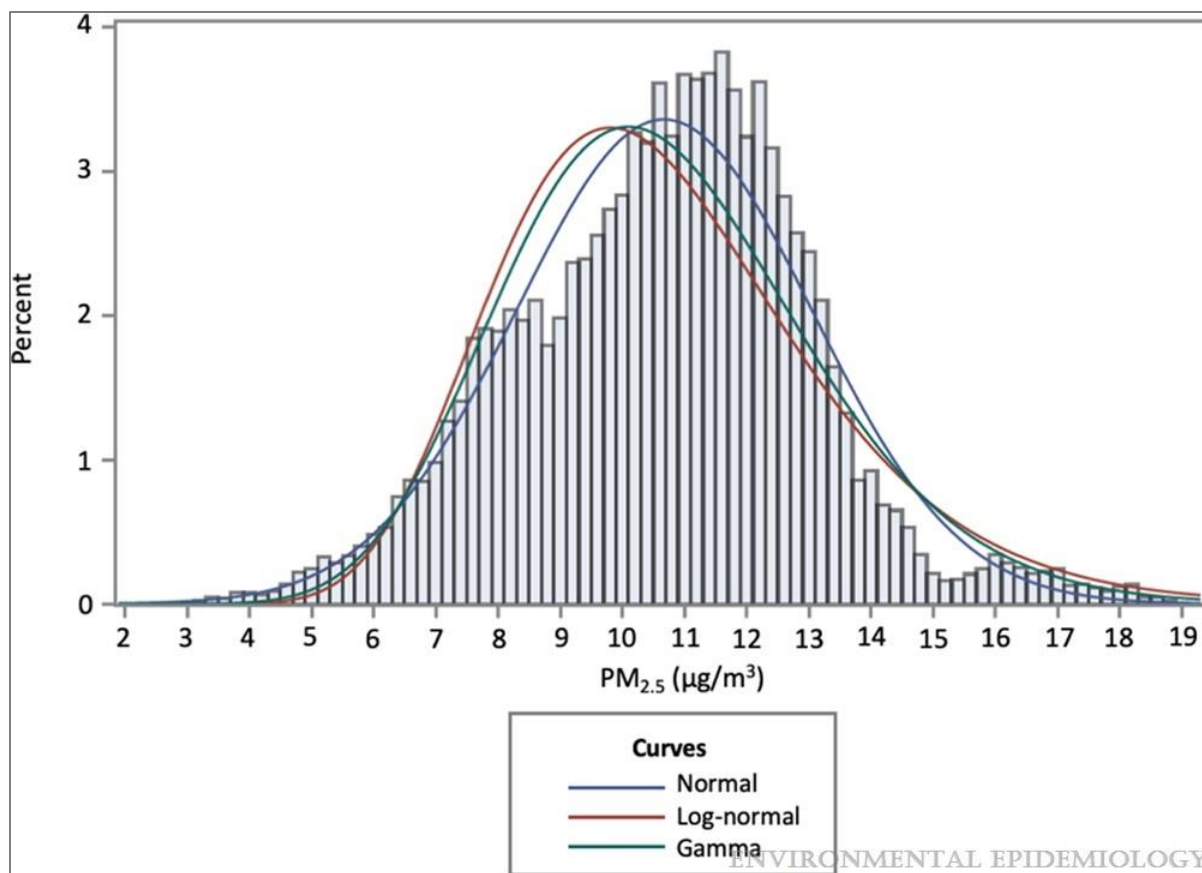


Figure 13. Modeled PM<sub>2.5</sub> Exposure Distribution for NHIS Study Population, with Select Fitted Probability Density Functions (from (Higbee, Lefler et al. 2020), publisher permission pending)

PM<sub>2.5</sub> concentrations reported in cohort studies are not equivalent to NAAQS design values (DVs). Information relating PM<sub>2.5</sub> concentrations from cohort studies discussed within this section to PM<sub>2.5</sub> DVs can be found in section 3.2 of the 2022 PM PA ((U.S. EPA 2022)).

#### 6.1.2.2 Estimating and Assigning Exposures in Epidemiology Studies

New developments in exposure assessment, including hybrid spatiotemporal models that incorporate satellite observations of AOD, land use variables, surface monitoring data from monitors, and chemical transport models, have led to improvements in the spatial resolution and extent of pollutant concentration surfaces. After reviewing the current state of exposure science, the 2019 PM ISA stated that “a number of studies demonstrate that the positive associations observed between long-term PM<sub>2.5</sub> exposure and mortality are robust to different methods of assigning exposure” and the 2020 O<sub>3</sub> ISA articulated that “hybrid methods have produced lower error predictions of ozone concentration compared with spatiotemporal models using land use and other geospatial data alone but may be subject to overfitting given the many different sources of data incorporated into the hybrid framework” ((U.S. EPA 2019)).

Although these advancements may reduce bias and uncertainty in risk estimates, the accuracy of hybrid exposure estimates can be difficult to confirm in areas lacking monitors. On the other hand, studies

using monitor data as the only exposure information have increasing exposure uncertainty the farther people live from the monitor site.

(Turner, Jerrett et al. 2016) and (Pope, Turner et al. 2015) analyzed the same ACS CSP-II population over the same time period but used different hybrid exposure estimation techniques. (Turner, Jerrett et al. 2016) used the hierarchical Bayesian space–time model (HBM) approach, which combines ambient measurement data with gridded estimates from the CMAQ photochemical model. (Pope, Turner et al. 2015) used a land use regression model with Bayesian Maximum Entropy kriging of residuals (LURBME). Sensitivity of the risk estimate to the exposure estimation technique is available in Table 33, including the estimate identified for the main benefits assessment in italics.

Table 33. PM<sub>2.5</sub>-Attributable ACS CSP-II Mortality Risk Estimates per 10 µg/m<sup>3</sup> from Different Exposure Estimation Techniques

Exposure Technique	Risk Estimate
<i>HBM</i>	<i>1.06 (1.04-1.08)</i>
LURBME	1.07 (1.06–1.09)

### 6.1.2.3 Confounding by O<sub>3</sub>

When considering the relationship between pollutant exposure and health effects, it can be informative to consider whether risk estimates are subjected to confounding when including other pollutants in copollutant models, especially when health impacts of more than two highly correlated pollutants are being estimated concurrently.<sup>79</sup> Regarding long-term exposures, the 2019 PM ISA concluded that “positive associations observed between long-term PM<sub>2.5</sub> exposure and total mortality remain relatively unchanged after adjustment for O<sub>3</sub>, NO<sub>2</sub>, and PM<sub>10-2.5</sub>” ((U.S. EPA 2019)).

Both (Turner, Jerrett et al. 2016) and (Di, Dai et al. 2017) provided single-pollutant and two-pollutant (including O<sub>3</sub> as a copollutant) PM<sub>2.5</sub>-attributable mortality risk estimates. Although the 2019 PM ISA found that, in general, PM<sub>2.5</sub> risk estimates were relatively unchanged to the inclusion of O<sub>3</sub> in copollutant models, a comparison of risk estimates that either do or do not include O<sub>3</sub> as a copollutant is included to clarify this potential sensitivity with respect to all-cause PM<sub>2.5</sub>-attributable mortality ((U.S. EPA 2019)). Differences in the magnitude of risk estimates including or excluding O<sub>3</sub> as a copollutant are provided in Table 34. Italicized risk estimates were identified for use in the main benefits assessment.

Table 34. Single- and Two-Pollutant (Including O<sub>3</sub> as a Copollutant) PM<sub>2.5</sub>-Attributable Mortality Risk Estimates per 10 µg/m<sup>3</sup>

	(Turner, Jerrett et al. 2016)	(Di, Dai et al. 2017)
<i>Two-Pollutant</i>	<i>1.06 (1.04-1.08)</i>	<i>1.073 (1.071, 1.075)</i>
Single-Pollutant	1.06 (1.04-1.08)	1.084 (1.081, 1.086)

### 6.1.2.4 Statistical Technique

Wu, 2020 reported hazard ratios estimated using causal inference approaches, wherein the authors “design the study creating a pseudo-population which mimics a randomized experiment...” Wu and co-authors applied three variants of the Generalized Propensity Score (GPS) technique: (1) matching by

<sup>79</sup> Modeling more than two correlated pollutants can be problematic due to collinearity issues.

GPS; (2) weighting by GPS; and (3) adjustment by GPS. Each of the three techniques provide similar Hazard Ratios, providing evidence that the results were robust to confounding (Table 35)

Table 35. Hazard Ratios per 10 µg/m<sup>3</sup> Estimated Using Three Causal Inference Approaches in (Wu, Braun et al. 2020)

<b>Causal Inference Technique</b>	<b>Hazard Ratio and 95% Confidence Interval</b>
Weighting	1.076 (1.065—1.088)
Matching	1.068 (1.054—1.083)
Adjustment	1.072 (1.061—1.082)

(Pope III, Lefler et al. 2019) also generated Cox proportional hazard estimates using both complex and basic models, of which the basic model did not account for complex survey design (using PHREG procedure in SAS version 9.3). The two estimates for all-cause mortality from long-term PM<sub>2.5</sub> exposures were nearly identical (Table 36).

Table 36. Complex and Basic Cox Proportional Hazard Model Estimates of PM<sub>2.5</sub>-Attributable Mortality per 10 µg/m<sup>3</sup>

	(Pope III, Lefler et al. 2019)
<i>Complex</i>	1.13 (1.11-1.16)
Basic	1.13 (1.11-1.15)

### 6.1.3 Asthma Onset in Children

For a number of health endpoints, we identified plausible alternative risk estimates to characterize the sensitivity of the main risk estimate to alternative assumptions and/or input parameters. Below we detail: 1) the endpoints for which we considered alternative risk estimates; and 2) the studies from which we drew the alternative risk estimates. This type of sensitivity assessment is also performed for other PM<sub>2.5</sub> and O<sub>3</sub> health endpoints in sections 6.1.4, 0, and 6.2.4.

The study identified as best characterizing risk for this health endpoint took place in Canada ((Tetreault, Doucet et al. 2016)). Even though comparatively (Tetreault, Doucet et al. 2016) was preferred in all identification criteria to other available studies (e.g., study size, exposure estimation technique, study period, etc.) other than location, we thought it useful to include the available U.S.-based risk estimates as uncertainty analyses. An overall comparison of the main risk estimate and 95% confidence interval from (Tetreault, Doucet et al. 2016) and the alternative risk estimates and confidence intervals from (McConnell, Islam et al. 2010) and (Nishimura, Galanter et al. 2013) can be found in Table 37. Details about the two studies providing alternate risk estimates is below.

Table 37. Potential Sensitivity of Estimated Instances of Asthma Onset

Potential Source of Uncertainty	Potential Insights Gained from Quantitative Uncertainty Analyses <sup>2</sup>
Application of Risk Estimates to Other Locations and Populations	(Tetreault, Doucet et al. 2016) included only Canadians whereas (Nishimura, Galanter et al. 2013) included five U.S. urban areas and (McConnell, Islam et al. 2010) was restricted to southern CA
Study Size	(Tetreault, Doucet et al. 2016) included the largest study size, approximately twenty-five times the size of either (Nishimura, Galanter et al. 2013) or (McConnell, Islam et al. 2010)
Study Period	(Tetreault, Doucet et al. 2016) evaluated the most recent health study period (1996-2011) compared to 2002-2006 for (McConnell, Islam et al. 2010) and 1986-2005 for (Nishimura, Galanter et al. 2013)
Exposure Estimate	(Tetreault, Doucet et al. 2016) used hybrid exposure estimates whereas sever states, whereas (Nishimura, Galanter et al. 2013) and (McConnell, Islam et al. 2010) used monitor-based estimates
Statistical Technique	(Tetreault, Doucet et al. 2016) and (McConnell, Islam et al. 2010) use time-varying and multilevel Cox proportional hazard models, respectively, whereas (Nishimura, Galanter et al. 2013) uses logistical regression models

Two of the five ISA-identified studies of asthma onset took place in the U.S. ((McConnell, Islam et al. 2010, Nishimura, Galanter et al. 2013)). (McConnell, Islam et al. 2010) examined the association between long-term traffic-related air pollution (PM<sub>2.5</sub>, PM<sub>10</sub>, O<sub>3</sub>, and NO<sub>2</sub>) exposure and incident asthma in children. The authors collected data for three years from a cohort of 2,497 kindergarten and first-grade children aged 4-9 who entered the Southern California Children’s Health Study without asthma or wheeze. (McConnell, Islam et al. 2010) defined new-onset asthma as physician-diagnosed asthma reported by parents on a yearly questionnaire. While the primary focus of the study was traffic-related air pollution from local vehicle emissions, the authors also utilized ambient air pollution exposure data from central site monitors in each of the 13 communities in the Southern California Children’s Health Study. The authors used a multilevel Cox proportional hazards model to estimate the association between ambient air pollution exposure and new-onset asthma, controlling for race/ethnicity, secondhand smoke exposure, and pets in the home. The identified hazard ratio of 1.66 (95% CI: 0.91-3.05) for a 17.4 µg/m<sup>3</sup> (range of exposure in the 13 communities) increase in annual average PM<sub>2.5</sub> exposure came from a single pollutant model.

The other study, (Nishimura, Galanter et al. 2013), investigated the relationship between long-term early-life pollution exposure (PM<sub>2.5</sub>, PM<sub>10</sub>, O<sub>3</sub>, NO<sub>2</sub>, and SO<sub>2</sub>) and asthma onset in 3,343 Latino and African American children in five urban areas (Chicago, IL; Bronx, NY; Houston, TX; San Francisco, CA; Puerto Rico). The authors obtained data from the Genes–environments and Admixture in Latino Americans (GALA II) Study and the Study of African Americans, Asthma, Genes and Environments (SAGE II). GALA II and SAGE II are case-control studies that enrolled children with and without asthma. The studies defined case subjects as children with physician-diagnosed asthma plus two or more symptoms of coughing, wheezing, or shortness of breath in the two years before study enrollment while control subjects were children with no reported history of asthma, lung disease, or chronic illness, and no reported symptoms of coughing, wheezing, or shortness of breath in the two years before study

enrollment. The authors estimated annual average pollution exposures during the first year of life as well as the first three years of life from self-reported residential histories by calculating inverse distance-squared weighted averages from the four closest U.S. EPA Air Quality System monitoring stations within 50 km. The authors first used regional- and study-specific logistic regression models to estimate the association between asthma diagnosis and pollution exposure, controlling for demographics and socioeconomic status and subsequently combined the regression coefficients into a multi-region estimate using a random-effects meta-analysis. The identified odds ratio of 1.03 (95% CI: 0.90-1.18) for a 1  $\mu\text{g}/\text{m}^3$  increase in average annual  $\text{PM}_{2.5}$  levels at the residential address during the first year of life came from a single pollutant model. Beta effect coefficients from the main (italicized) and sensitivity analyses are available in Table 38.

Table 38. Beta Coefficients and Standard Errors (SE) from Studies of Examining Long-term  $\text{PM}_{2.5}$  Exposure and New Onset Asthma in Children

<b>Study</b>	<b>Age Range</b>	<b>Beta Coefficient (SE)</b>
<i>(Tetreault, Doucet et al. 2016)</i>	0-17	0.044 (0.0009)
(McConnell, Islam et al. 2010)	4-17	0.029 (0.017)
(Nishimura, Galanter et al. 2013)	7-21	0.030 (0.069)

#### 6.1.4 Cardiovascular Hospital Admissions

(Bell, Son et al. 2015) was identified as best characterizing risk across the U.S. for benefits assessment purposes as it included the largest study size, most recent time period, and a nationally representative geographic area. However, it was restricted to ages >64 and based exposure estimates solely on monitoring data. There was also another large study of  $\text{PM}_{2.5}$ -attributable cardiovascular hospital admission impacts that included all ages and incorporated hybrid exposure estimation techniques ((Talbot, Rager et al. 2014)). Differences in the age ranges and ICD-9 codes prevented pooling of the two estimates but comparing the two estimates could provide insights into uncertainties associated with epidemiologic estimates of this health endpoint (Table 39). Therefore, we include a risk estimate of cardiovascular hospital admission impacts from long-term  $\text{PM}_{2.5}$  exposure from (Talbot, Rager et al. 2014) as a sensitivity analysis of this health endpoint (Table 40). Please note that (Talbot, Rager et al. 2014) provides individual risk estimates for each state, which will be pooled into a single estimate to compare with (Bell, Son et al. 2015).

(Talbot, Rager et al. 2014) assessed daily  $\text{PM}_{2.5}$  concentrations and hospitalizations for cardiovascular disease in Florida, Massachusetts, New Hampshire, New Jersey, New Mexico, New York, and Washington from 2001 to 2008. The authors gathered hospital discharge data from each state's respective data stewards. (Talbot, Rager et al. 2014) conducted a time-stratified case crossover study using hospitalization data for all cardiovascular diseases (ICD-9 390-459) and for several specific cardiovascular diseases within the ICD-9 390-459 range. Authors used a downscaling Bayesian space-time modeling approach to combine air monitoring data and air gridded numerical outputs from CMAQ to predict daily  $\text{PM}_{2.5}$  concentrations. The authors gathered meteorological data from the Centers for Disease Control (CDC) Wonder North America Land Data Assimilation System Daily Air Temperatures and Heat Index. Risk estimates were presented for a 10  $\mu\text{g}/\text{m}^3$  increase in  $\text{PM}_{2.5}$  for each state and season across three single-day lags (0, 1, and 2) and a three-day lag average (0-2) by diagnosis. All-year risk estimates were identified over season-specific estimates and estimates of multiday average lag

period were identified over single-day lag estimates.<sup>80</sup> The seven state-specific risk estimates identified as sensitivity analyses were pooled using the random or fixed effects algorithm in BenMAP-CE.<sup>81</sup> The seven risk estimates reflect a mix of positive and negative values. State-specific risk estimates identified from (Talbot, Rager et al. 2014) come from a two-pollutant multivariable model including O<sub>3</sub> of ICD-9 codes 390-459: 1.005 (95% CI: 0.998-1.012) for Massachusetts; 1.011 (95% CI: 1.007-1.016) for New Jersey; 1.011 (95% CI: 0.973-1.050) for New Mexico; and 1.011 (95% CI: 1.008-1.014) for New York. Each odds ratio is for a 10 µg/m<sup>3</sup> increase in the averaged daily mean PM<sub>2.5</sub> concentration 0-, 1-, and 2-day lags ((Talbot, Rager et al. 2014), Table 3). Beta effect coefficients from the main (italicized) and sensitivity analyses are available in Table 40.

Table 39. Potential Sensitivity of Estimated Cardiovascular Hospital Admissions

Potential Source of Uncertainty	Potential Insights Gained from Quantitative Uncertainty Analyzes
Application of Risk Estimates to Other Locations and Populations	(Talbot, Rager et al. 2014) included all ages whereas (Bell, Son et al. 2015) was restricted to ages >64
Confounding by Individual Risk Factors (Location)	(Talbot, Rager et al. 2014) was restricted to seven states, (Bell, Son et al. 2015) included all states
Confounding by Other Pollutants	(Talbot, Rager et al. 2014) included the copollutant O <sub>3</sub>
Exposure Estimate	(Talbot, Rager et al. 2014) used hybrid exposure estimates whereas sever states, (Bell, Son et al. 2015) used monitor-based estimates

Table 40. PM<sub>2.5</sub>-Attributable Cardiovascular Hospital Admissions Beta Estimates

Study	Beta Coefficient (SE)
<i>(Bell, Son et al. 2015)</i>	<i>0.00065 (0.00009)</i>
(Talbot, Rager et al. 2014), MA	MA: 0.00050 (0.00035), NJ: 0.00109 (0.0002), NM: 0.00109 (0.0019), NY: 0.00109 (0.00015), FL: -0.00040 (0.0003), NH: -0.00121 (0.0012), WA: -0.00090 (0.0005)

A study from the 2020 PM ISA Supplement also evaluated cardiovascular hospital admissions. (Danesh Yazdi, Wang et al. 2021) examined the relationship between long-term ambient air pollution (NO<sub>2</sub>, O<sub>3</sub>, PM<sub>2.5</sub>) exposure and hospital admissions for four cardiovascular and respiratory outcomes among 63,006,793 Medicare beneficiaries over the age of 64 in the contiguous U.S. The authors retrieved data from the Medicare denominator file and the Medicare Provider Analysis and review file, including all

<sup>80</sup> Lag period preference identification criteria is more fully described in 2019 PM ISA Appendix Table A-1.

<sup>81</sup> Random or fixed effects pooling is a method to combine two or more distributions into a single new distribution, allowing for the possibilities that either 1) a single true underlying relationship exists between the component distributions, and that differences among estimated parameters are the result of sampling error, or 2) the estimated parameter from different studies may in fact be estimates of different parameters, rather than just different estimates of a single underlying parameter, and weights for the pooling are generated via inverse variance weighting, thus giving more weight to the studies that exhibit lower variance and less weight to the input distributions with higher variance.

hospital admissions from 2000 through 2016 with primary discharge codes for myocardial infarction, ischemic stroke, atrial fibrillation and flutter, and pneumonia. They modeled PM<sub>2.5</sub> exposure at a 1-km<sup>2</sup> scale using high-resolution spatiotemporal models that combined three machine learning algorithms using land use terms, chemical transport model predictors, meteorologic variables, and satellite measurements and validating against monitor data. (Danesh Yazdi, Wang et al. 2021) employed doubly robust additive models (DRAM), which account for confounding through inverse probability weights of exposure and adjustment in the outcome regression model. They examined the relationship between hospital admissions for myocardial infarction, ischemic stroke, atrial fibrillation and flutter, or pneumonia and each of three ambient air pollutants, adjusting each model for individual, socioeconomic, and behavioral covariates as well as the other two pollutants. Because we were unable to obtain validated Hazard Ratios from this study, we elected not to include it in our primary analysis.

Similar to cardiovascular hospital admissions, there was an estimate of PM<sub>2.5</sub>-attributable respiratory hospital admissions that included all ages and utilized a hybrid exposure estimation approach, but was geographically limited, in this case to a single state. However, we thought it useful to include this estimate as a sensitivity analysis due to the contrasts between it and the italicized main benefits estimates (Table 41 and Table 42). As compared to PM<sub>2.5</sub>-attributable mortality and cardiovascular hospital admission impact estimates, there may be greater uncertainty associated with estimates of PM<sub>2.5</sub>-attributable respiratory hospital admissions (Table 42).

(Jones, Diez-Roux et al. 2015) encompassed all ages, races, and ethnicities with a case-crossover analysis in New York state, using 24-hour average PM<sub>2.5</sub> concentrations from CMAQ and meteorological data from the National Climactic Data Center. The authors assessed hospital discharge data from the New York State Department of Health State Planning and Research Cooperative System through principle diagnosis categorized by ICD-9 code (chronic bronchitis (ICD-9 491), emphysema (ICD-9 492), asthma (ICD-9 493), and chronic airway obstruction (ICD-9 496). Authors used a single pollutant conditional logistic regression model to analyze the respiratory hospital admission and PM<sub>2.5</sub> chemical constituent data over time and by season. The authors calculated hazard ratios using SAS (version 9.2) with 95% confidence intervals from the regression models. The estimate best characterizing U.S. risk comes from the 4-day lag all-year PM<sub>2.5</sub> estimate in Figure 2a: 1.006 (1.004-1.009). Please note, this risk estimate was derived from the figure, as the exact numbers were not provided in the paper and the authors did not respond to our request.

Table 41. Potential Respiratory Hospital Admission Sensitivity Insights

Potential Source of Uncertainty	Potential Insights Gained from Quantitative Uncertainty Analyzes <sup>2</sup>
Application of Risk Estimates to Other Locations and Populations	(Jones, Diez-Roux et al. 2015) included all ages whereas (Bell, Son et al. 2015) was restricted to ages >64
Confounding by Individual Risk Factors (Location)	(Jones, Diez-Roux et al. 2015) was restricted to a single state, (Bell, Son et al. 2015) included all states
Exposure Estimate	(Jones, Diez-Roux et al. 2015) used hybrid exposure estimates, whereas (Bell, Son et al. 2015) used monitor-based estimates



Table 42. PM<sub>2.5</sub>-Attributable Respiratory Hospital Admissions Beta Risk Estimates

Study	Age Range	Beta Coefficient (SE)
<i>(Bell, Son et al. 2015)</i>	65-99	0.00025 (0.0001)
<i>(Ostro, Malig et al. 2016)</i>	0-18	0.00275 (0.0008)
<i>(Jones, Diez-Roux et al. 2015)</i>	0-99	0.00080 (0.0002)

One study analyzed the effects of long-term PM<sub>2.5</sub> exposure on cardiovascular hospital admissions with PM<sub>2.5</sub> exposures. (Kloog, Coull et al. 2012) collected medical data from 67,678 adults aged 65 to 99 in the U.S. Medicare program database from 2000 to 2006. They defined all respiratory, cardiovascular disease, stroke, and diabetes based on emergency department visits and primary discharge diagnosis records. Authors used a hybrid exposure technique comprised of daily PM<sub>2.5</sub> concentration data from aerosol optical depth (AOD) measurements and ambient air monitors from the U.S. EPA and Interagency Monitoring of Protected Visual Improvements (IMPROVE). Authors also obtained land use regressions, meteorological data (National Climatic Data Center), and socioeconomic data (U.S. Census Bureau) matched to zip codes. Utilizing land use Poisson regression single-pollutant models, the authors found an 3.49% (95% CI: 0.09-5.18) increase in stroke incidence for a 10 µg/m<sup>3</sup> increase in the 7-year mean PM<sub>2.5</sub> concentrations. However, as the study area was restricted to New England (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont) from 2000 to 2006, this study serves only as an exposure duration sensitivity analysis for the main benefits assessment endpoints.

#### 6.1.4.1 Emergency Hospital Admissions (EHAs)

Interestingly, a substantial subset of the ISA-identified recent epidemiologic literature evaluating respiratory hospitalizations restricted analyses to emergency hospital admissions (EHAs), defined as hospitalizations admitted from the emergency department (section 3.2). Due to time and resource requirements, we were unable to develop county-level baseline incidence data for EHAs, in addition to total hospital admissions. However, as we were interested in how estimates of EHAs compared to total, we include a risk estimate of respiratory EHAs from (Zanobetti, Franklin et al. 2009) using national baseline incidence data. Though the EHA estimate came from a smaller and older study than the main analysis respiratory hospital admission study, the EHA estimate is nearly an order of magnitude larger than the risk estimate included in the main estimate (*italicized*).

Table 43. Comparison of the PM<sub>2.5</sub>-Attributable Respiratory Hospital Admissions Beta Risk Estimate to the EHA Respiratory Estimate

Study	Beta Coefficient (SE)
<i>(Bell, Son et al. 2015)</i>	0.00025 (0.0001)
<i>(Zanobetti, Franklin et al. 2009)</i>	0.00204 (0.0004)

#### 6.1.5 Hypertension

The 2022 PM ISA Supplement states that “[r]ecent studies add to the evidence providing support for positive associations among post-menopausal women and referenced four epidemiologic studies meeting the minimum criteria (section 2.1.1) of PM<sub>2.5</sub>-attributable hypertension ((U.S. EPA 2022)). Additionally, we identified a recent publication estimating the lifetime COI for incidence hypertension

(section 6.1.5.2). However, we include hypertension only as a sensitivity analysis here due to the limited evidence available in the 2019 PM ISA and 2022 Supplement to the ISA ((U.S. EPA 2019, U.S. EPA 2022)). Specifically:

*The literature assessed in the 2019 PM ISA provided evidence of associations between long-term PM<sub>2.5</sub> exposure and hypertension. Recent studies are generally consistent with this assessment, reporting positive associations among post-menopausal women enrolled in the WHI study and in cardiac catheterization patients. However, no association between long-term PM<sub>2.5</sub> exposure and hypertension was observed among Black women enrolled in the JHS.*

### **6.1.5.1 Identification of Epidemiologic Studies and Risk Estimates**

#### 6.1.5.1.1 Available Epidemiologic Literature

The 2022 supplement to the PM ISA identified three epidemiologic studies of hypertension that met the minimum identified criteria above ((U.S. EPA 2022), section 2.1.1).

#### 6.1.5.1.2 Identifying Suitable Studies for Use in Benefits Assessments

Of the three available studies, one was more representative of the U.S. with respect to the population observed and the geographic scope ((Honda, Eliot et al. 2017)).

6.1.5.1.3 Studies and Risk Estimates Identified as Most Suitable for Use in Benefits Assessments (Honda, Eliot et al. 2017) studied the association between long-term PM<sub>2.5</sub> exposure and incident hypertension in a cohort of 44,255 post-menopausal (aged 50-79 years at baseline) women enrolled in the Women's Health Initiative (WHI) clinical trials nationwide who were free of hypertension at baseline. Authors defined incident hypertension as systolic blood pressure  $\geq 140$  mmHg, diastolic blood pressure  $\geq 90$  mmHg, or self-reported anti-hypertensive medication use, and participants were followed from enrollment until 2010 for a total of 298,383 person-years of follow-up. (Honda, Eliot et al. 2017) employed a hybrid modeling technique using daily PM<sub>2.5</sub> measurements and geographic covariates to calculate annual moving average estimates of PM<sub>2.5</sub>, PM<sub>10</sub>, and PM<sub>10-2.5</sub> exposure for each participant. They modeled the association between hypertension incidence and particulate matter exposure using single-pollutant and two-pollutant (PM<sub>2.5</sub> and PM<sub>10-2.5</sub>) Cox proportional hazards models that adjusted for numerous individual-level covariates, clinical trial treatment arm, and WHI study clinical site.

### **6.1.5.2 Identification of Valuation Estimates**

The lifetime cost-of-illness (COI) for incidence hypertension is derived from (Kirkland, Heincelman et al. 2018), who estimate the annual out-of-pocket expenditures associated with high blood pressure among adults ages 45 and older in the United States. The authors utilize data from the Medical Expenditures Panel Survey (MEPS) from 2003-2014 and identify patients with hypertension using the ICD-9 code 401.xx. Cost elements include inpatient, outpatient, and emergency room services as well as prescription medicine expenses. The authors adjust annual expenses such that they reflect the incremental expenditures for individuals with hypertension versus without hypertension. They calculate an annual cost of \$1,850 (\$2015) associated with hypertension. To calculate the lifetime costs of hypertension we calculate the costs incurred over 20 years, reflective of the rounded age-weighted life-expectancy of women diagnosed with hypertension in Canada ((Loukine, Waters et al. 2011)). The continuing annual costs are discounted by three or seven percent. Over 20 years, the total medical costs are calculated as \$28,348 using a 3 percent discount rate and \$20,970 using a 7 percent discount rate.

### 6.1.6 Effect Modification of Health Effects in At-Risk Populations<sup>82</sup>

ISAs typically include an assessment of the weight of evidence demonstrating that certain subpopulations experience increased mortality or morbidity risks from air pollutant exposure compared to other groups. This is also known as effect modification and occurs when the measure of an effect changes across levels of a variable other than PM<sub>2.5</sub> exposure. The 2019 PM ISA examined toxicological, controlled human exposures, and epidemiologic literature considering whether certain populations and lifestages might be at increased risk of air pollutant-related health effects ((U.S. EPA 2019)).

The ISAs categorize relationships between exposure and effect modification for various population and lifestages into the following four groups:

- *Adequate* evidence: There is substantial, consistent evidence within a discipline to conclude that a factor results in a population or lifestage being at increased risk of air pollutant-related health effect(s) relative to some reference population or lifestage. Where applicable, this evidence includes coherence across disciplines. Evidence includes multiple high-quality studies.
- *Suggestive* evidence: The collective evidence suggests that a factor results in a population or lifestage being at increased risk of air pollutant-related health effect(s) relative to some reference population or lifestage, but the evidence is limited due to some inconsistency within a discipline or, where applicable, a lack of coherence across disciplines.
- *Inadequate* evidence: The collective evidence is inadequate to conclude whether a factor results in a population or lifestage being at increased risk of air pollutant-related health effect(s) relative to some reference population or lifestage. The available studies are of insufficient quantity, quality, consistency, and/or statistical power to permit a conclusion to be drawn.
- *Evidence of no effect*: There is substantial, consistent evidence within a discipline to conclude that a factor does not result in a population or lifestage being at increased risk of air pollutant-related health effect(s) relative to some reference population or lifestage. Where applicable, the evidence includes coherence across disciplines. Evidence includes multiple high-quality studies.

Presenting PM<sub>2.5</sub>-attributable benefit estimates stratified by the value of another covariate can provide insight into risk within various population subgroups. To accomplish this, we reviewed relevant chapters from the 2019 PM ISA in order to compile and assess studies cited in support of the Agency's determinations, focusing on studies referenced in Table 12-3 for population characteristics with either "adequate evidence" (i.e., substantial, consistent evidence) or "suggestive evidence" (i.e., limited evidence due to inconsistency or a lack of coherence in research) of increased risk (sections 6.1.6.1 and 6.1.6.2) ((U.S. EPA 2019)). The factors with "adequate evidence" for PM<sub>2.5</sub> are lifestage (children) and race (nonwhite populations), while the factors with "suggestive evidence" are pre-existing disease (cardiovascular disease, respiratory disease, and obesity), genetic factors (variant genotypes), low socioeconomic status, and smoking.

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<sup>82</sup> Analyses of effect modification will not be included in the main analyses, so as to avoid the possibility of double-counting impacts. This potential uncertainty could also be described as the effect modification of individual risk factors.

### 6.1.6.1 Study and Risk Estimate Identification Criteria for Populations At-Risk for PM<sub>2.5</sub> Exposures

We identified all studies in the related section of PM ISA Chapter 12 for each at-risk factor listed above, resulting in a set of 123 studies for at-risk populations ((U.S. EPA 2019)). This collection includes the following number of studies, with some studies duplicated for multiple endpoints.

- 8 studies for lifestage (children),
- 25 studies for race (nonwhite populations),
- 67 studies for pre-existing disease across disease types,
- 18 studies for genetic factors,
- 25 studies for socioeconomic status, and
- 14 studies for smoking.

We then focused our review on the risk factors with “adequate evidence”, due to stronger supporting evidence as well as because they could be evaluated using currently available data. We extracted study information from all studies with “adequate evidence” and applied initial screening criteria to identify peer-reviewed, epidemiological studies focused on PM<sub>2.5</sub> conducted in the US or Canada. We also documented the mortality and/or morbidity health endpoints included in each study, focusing on all-cause mortality and respiratory morbidity endpoints. We then evaluated the group of remaining studies based on additional identification criteria built off the criteria for the primary analysis, described in Table 44.

Table 44. PM<sub>2.5</sub> At-Risk Study Identification Criteria

Criteria	Description
Peer-Review	Peer-reviewed research exclusively
Study design	Epidemiological study
PM <sub>2.5</sub> Study	PM <sub>2.5</sub> exposure rather than other PM <sub>10</sub> or other sizes
Study Location	US or Canada
Study Duration	Long-term studies preferred
Population Attributes	Presents risk estimates for clearly defined at-risk groups for which data currently exist in BenMAP-CE
Causal or Likely Causal Health Effects	Adequate evidence for at-risk groups in ISA
Economically Valuable Health Effects	Health endpoints for which economic values have been or could reasonably be developed
Baseline Incidence Data	Must be able to identify baseline incidence data for subpopulations

### 6.1.6.2 All-Cause Mortality

For the mortality endpoint, seven all-cause mortality studies for the nonwhite population met our criteria. No mortality studies for the child at-risk group met the initial screening criteria. Of the seven studies of nonwhite populations, three were short-term exposure studies relating daily PM<sub>2.5</sub> exposure and daily deaths and four were long-term exposure studies relating annual PM<sub>2.5</sub> exposure and annual mortality. Consistent with the main benefits assessment, we focused on the following four long-term studies as long-term exposure studies may include some effects of short-term exposures (section

2.3.1.1): (Di, Wang et al. 2017), (Kioumourtzoglou, Schwartz et al. 2016), (Parker, Kravets et al. 2018), and (Wang, Shi et al. 2017).

We evaluated specific details of risk estimates provided by each study to determine if sufficient information exists for use in a quantitative sensitivity analysis. Of the studies, only (Di, Wang et al. 2017) provided sufficient information to apply risk models quantifying increased risks to nonwhite groups, including non-Hispanic white, Black, Asian, American Indian, and Hispanic-white populations. Additional detail on the study can be found in section 2.3.1.1.3.1.2 or in the associated Study Information Table.

We applied similar criteria to morbidity endpoints for the child and nonwhite at-risk groups. No studies cited for the child subgroup met our criteria for inclusion, and one endpoint, emergency room visits for asthma, was chosen for quantification for the nonwhite populations at-risk factor group. The study we chose to evaluate was (Alhanti, Chang et al. 2016), which presents risk information for white and pooled nonwhite populations disaggregated into five age groups.

We developed BenMAP-ready Health Impact Functions for each at-risk group described by (Di, Wang et al. 2017) and (Alhanti, Chang et al. 2016), summarized in Table 45.

Table 45. Identified PM<sub>2.5</sub> At-Risk Beta Coefficients and Standard Errors

At-Risk Factor	Endpoint	Study	Population Demographic	Beta Coefficient (SE)
Race, nonwhite populations	Morality, All Cause	(Di, Wang et al. 2017)	White	0.0061 (0.0001)
			Hispanic	0.0110 (0.0008)
			Black	0.0189 (0.0004)
			Asian	0.0092 (0.0010)
			American Indian	0.0095 (0.0019)
Race, nonwhite populations	Morality, All Cause	(Pope III, Lefler et al. 2019)	Non-Hispanic White	0.001806 (0.00184)
			Hispanic	0.004084 (0.00403)
			Non-Hispanic Black	0.005064 (0.00485)
			Other/unknown	0.007732 (0.00788)
Race, nonwhite populations	Emergency Room Visits, Asthma	(Alhanti, Chang et al. 2016)	White, age 0-4	0.0025 (0.0019)
			Nonwhite, age 0-4	0.0037 (0.0012)
			White, age 5-18	0.0025 (0.0016)
			Nonwhite, age 5-18	0.0049 (0.0012)

## 6.2 QUANTITATIVE CHARACTERIZATION OF O<sub>3</sub> UNCERTAINTIES AND EVALUATING SENSITIVITY TO ALTERNATE O<sub>3</sub> ASSUMPTIONS

### 6.2.1 Statistical Uncertainty Around the Risk Estimate (Monte-Carlo Assessment)

For all endpoints analyzed, we use a Monte Carlo simulation in which we sample from the standard error associated with each risk estimate and present the resulting 2.5<sup>th</sup> and 97.5<sup>th</sup> percentile values from this distribution as a 95<sup>th</sup> percentile confidence interval around the estimated health impact and monetized health benefits. Monte Carlo methods are a well-established means of characterizing random sampling error associated with the risk estimates from epidemiologic studies. This approach randomly samples from a distribution of incidence and valuation estimates to characterize the effects of uncertainty on output variables. The reported standard errors in the epidemiologic studies determined the distributions for individual effect estimates for endpoints estimated using a single study. For endpoints estimated using a pooled estimate of multiple studies, the confidence intervals reflect both the standard errors and the variance across studies. The confidence intervals around the monetized benefits incorporate the standard errors from the epidemiologic risk estimate as well as the distribution of the valuation function. These confidence intervals do not reflect other sources of uncertainty inherent within the estimates, such as baseline incidence rates, populations exposed, and transferability of the effect estimate to diverse locations. As a result, the reported confidence intervals and range of estimates give an incomplete picture about the overall uncertainty in the benefits estimates.

### 6.2.2 Respiratory Mortality

#### 6.2.2.1 Confounding by PM<sub>2.5</sub>

When considering the relationship between pollutant exposure and health impacts, it can be informative to consider whether risk estimates are changed when other pollutants are included in copollutant models, especially when health impacts of multiple pollutants are being estimated concurrently. While no conclusions were formed regarding the impact of copollutant confounding on long-term exposure-related respiratory mortality, the 2020 O<sub>3</sub> ISA found that “positive associations observed between long term O<sub>3</sub> exposure and total mortality remain relatively unchanged after adjustment for PM<sub>2.5</sub> and NO<sub>2</sub>” ((U.S. EPA 2020)).

(Turner, Jerrett et al. 2016) provided single- and multipollutant (including PM<sub>2.5</sub> as a copollutant) O<sub>3</sub>-attributable respiratory mortality risk estimates. A comparison of risk estimates that either do or do not include PM<sub>2.5</sub> as a copollutant is included to clarify this potential sensitivity with respect to O<sub>3</sub>-attributable respiratory mortality. Differences in the magnitude of risk estimates including or excluding PM<sub>2.5</sub> as a copollutant are provided in Table 46.

Table 46. Single- and Two-Pollutant (Including PM<sub>2.5</sub> as a Copollutant) Long-Term O<sub>3</sub>-Attributable Respiratory Mortality Risk Estimates per 10 ppb

Study	Single-Pollutant	Multipollutant
(Turner, Jerrett et al. 2016)	1.14 (1.10-1.18)	1.12 (1.08-1.16)

### 6.2.2.2 Short-Term O<sub>3</sub> Exposures

#### 6.2.2.2.1 Potential Threshold Analysis

The 2020 final O<sub>3</sub> ISA evaluated a number of studies examining the shape of the concentration-response relationship for short-term O<sub>3</sub> exposure and total/nonaccidental mortality, which we use to inform the long-term O<sub>3</sub>-attributable respiratory mortality relationship ((U.S. EPA 2020)). The O<sub>3</sub> ISA found that “studies that used different statistical approaches and ozone averaging times (i.e., 24 hour avg and 8 hour max) provide evidence of a linear concentration-response relationship, with less certainty in the shape of the curve at lower concentrations [i.e., ...30 ppb for 8 hour max], [although] an examination of whether a threshold exists in the ozone mortality concentration-response relationship provided no evidence of a concentration below which mortality effects do not occur when examining 5 µg/m<sup>3</sup> (~2.55 ppb) increments across the range of 1 hour max concentrations reported in the U.S. and Canadian cities included in [a large cohort].” As the (Zanobetti and Schwartz 2008) risk estimate uses the MDA8 metric, it can be used to quantitatively assess the effect of an O<sub>3</sub> threshold at 30 ppb would have on benefits estimates. For context, approximately 3.7% of the contiguous U.S. population is projected to reside in areas where MDA8 O<sub>3</sub> concentrations are annually below 30 ppb in 2024 ((U.S. EPA 2020)). Clinical evidence provides little indication that adverse effects occur at extremely low levels in most individuals. Epidemiologic evidence is qualitatively discussed further in section 6.5.15.2.

#### 6.2.2.2.2 Confounding by PM

Regarding short-term exposures, the 2020 O<sub>3</sub> ISA found that “the few recent multicity studies that examined potential copollutant confounding provide evidence supporting that O<sub>3</sub> mortality risk estimates are relatively unchanged or slightly attenuated, but remain positive, in copollutant models with PM<sub>2.5</sub>, PM<sub>10</sub>, and NO<sub>2</sub>.”

(Katsouyanni, Samet et al. 2009) provided single- and two-pollutant (including PM<sub>10</sub> as a copollutant) short-term O<sub>3</sub>-attributable respiratory mortality risk estimates for a subset of 15 of the 86 cities analyzed. A comparison of risk estimates that either do or do not include PM<sub>10</sub> as a copollutant is included to clarify this potential sensitivity with respect to O<sub>3</sub>-attributable respiratory mortality. Differences in the magnitude of risk estimates including or excluding PM<sub>2.5</sub> as a copollutant are provided in Table 47. Please note, as distributed lag risk estimates were not provided for the two-pollutant analyses, in addition to the inclusion of PM<sub>2.5</sub> as a copollutant and the number of cities analyzed, there is a difference in the lag duration between the estimates in Table 47.

Table 47. Single- and Two-Pollutant (Including PM<sub>10</sub> as a Copollutant) Short-Term O<sub>3</sub> Exposure O<sub>3</sub>-Attributable Excess Premature Respiratory Mortality Risk Estimates per 10 ppb

Study	Single-Pollutant	Two-Pollutant
(Katsouyanni, Samet et al. 2009)	0.77% (0.17%, 1.37%)	0.99% (-0.33%, 2.31%)

### 6.2.3 All-Cause Mortality

When estimating air pollutant-attributable health impacts, EPA focuses on endpoints for which the underlying scientific evidence is strongest. That is, when evaluating evidence across scientific disciplines (i.e., clinical, animal toxicological, and epidemiologic) there is often consistency of effects within a discipline, coherence of effects across disciplines, and evidence of biological plausibility. Such an approach gives us greater confidence in the relationship between exposure and health outcome. For

criteria pollutants, EPA typically relies upon the causality determinations in the latest ISA or equivalent, which are made using a weight-of evidence approach. Generally, to estimate the pollutant-attributable human health benefits in which we are most confident, we at least assess health effects identified as having a ‘causal’ or ‘likely to be causal’ relationship with the pollutant of interest in the most recently published ISA. This is not to imply there may not be benefits associated with endpoints having a “suggestive of, but not sufficient to infer, a causal relationship,” but rather that there is greater uncertainty in these potential benefits.

Because of the significance of the endpoint, we include a limited quantitative sensitivity analysis of total mortality associated with long-term O<sub>3</sub> exposure. While the 2020 O<sub>3</sub> ISA concluded that evidence was “suggestive of, but not sufficient to infer,” a causal relationship between long-term exposures and total mortality, the reduction of this risk is likely still valuable to society ((U.S. EPA 2020)). As such, for this sensitivity discussion, we include risk estimates of long-term, all-cause O<sub>3</sub>-attributable total mortality from the two studies used to estimate PM<sub>2.5</sub>-attributable mortality risk (Table 48). Please note these long-term, all-cause risk estimates include respiratory mortality estimates and should not be added to the respiratory mortality estimates.

Table 48. Long-Term O<sub>3</sub>-Attributable Total Mortality Risk Estimates per 10 ppb

Study	Risk Estimate (per 10 ppb increase in O <sub>3</sub> )	Risk Estimate Details
(Turner, Jerrett et al. 2016)	1.02 (1.01-1.03)	Fully adjusted HBM multipollutant estimate from Table E9, ages 35-99
(Di, Wang et al. 2017)	1.011 (1.010, 1.012)	GEE two-pollutant main analysis estimate from Table 2, ages 65-99

#### 6.2.4 Asthma Onset in Children

The study identified as best characterizing risk for asthma onset in children was conducted in Canada ((Tetreault, Doucet et al. 2016)). Even though comparatively (Tetreault, Doucet et al. 2016) was preferred in identification criteria to other available studies (e.g., study size, exposure estimation technique, etc.) other than location and study period, we thought it useful to include the largest and most recent U.S.-based risk estimates as a sensitivity analysis. An overall comparison of the main risk estimate from (Tetreault, Doucet et al. 2016) and the alternative risk estimates from (Garcia, Berhane et al. 2019) can be found in Table 49. Details about the study providing an alternate risk estimate is below.



Table 49. Potential Sensitivity of Estimated Instances of Asthma Onset

Potential Source of Uncertainty	Potential Insights Gained from Quantitative Uncertainty Analyses <sup>2</sup>
Application of Risk Estimates to Other Locations and Populations	(Tetreault, Doucet et al. 2016) included only Canadians whereas (Garcia, Berhane et al. 2019) was restricted to southern CA
Study Size	(Tetreault, Doucet et al. 2016) included the largest study size, approximately twenty-five times the size of (Garcia, Berhane et al. 2019)
Study Period	(Garcia, Berhane et al. 2019) evaluated a more recent and longer health study period (1993-2014) compared to 2002-2011 for (Tetreault, Doucet et al. 2016)
Exposure Estimate	(Tetreault, Doucet et al. 2016) used hybrid exposure estimates whereas sever states, whereas (Garcia, Berhane et al. 2019) used monitor-based estimates
Statistical Technique	(Tetreault, Doucet et al. 2016) used time-varying Cox proportional hazard models, whereas (Garcia, Berhane et al. 2019) uses Poisson log-linear regression models

Three of the four ISA-identified studies of long-term O<sub>3</sub>-attributable asthma onset took place in the U.S., although only one included a study period more recent than 2005 ((Garcia, Berhane et al. 2019)). (Garcia, Berhane et al. 2019) examined the associations between long-term ozone exposure and asthma onset in children (aged nine-18 years) with no history of asthma in Southern California. The authors followed three waves of participants from the Children's Health Study for eight years between 1993 and 2014. (Garcia, Berhane et al. 2019) obtained health and demographic data from parents, guardians, or participants, who completed questionnaires annually. In order to calculate annual mean, community-level ozone exposure, the authors acquired daily eight-hour mean O<sub>3</sub> concentrations through ambient air pollution monitors. Multi-level Poisson regression models with one-year lag showed no statistically significant associations between long-term O<sub>3</sub> exposure and asthma onset in children. Models adjusted for demographic variables as well as factors pertaining to family medical history, environmental factors, and near-roadway pollution.

The magnitudes of main and alternate risk estimates of long-term O<sub>3</sub> exposure and asthma onset in children provided in Table 50.

Table 50. Long-Term O<sub>3</sub>-Attributable Asthma Beta Coefficients

Study	Beta Coefficient	Age Range
(Tetreault, Doucet et al. 2016)	0.020754	0-17
(Garcia, Berhane et al. 2019)	0.01695	9-18

### 6.2.5 Effect Modification of Health Effects in At-Risk Populations<sup>83</sup>

Effect modification was also investigated with regard to O<sub>3</sub> exposures. We reviewed relevant chapters from 2020 O<sub>3</sub> ISA and used a similar method to that described for PM<sub>2.5</sub> to compile and assess studies cited in support of the Agency's determinations ((U.S. EPA 2020), section 6.1.6). As the 2020 O<sub>3</sub> ISA only presents an evaluation of at-risk groups in summary form and extensively references the findings from the 2013 O<sub>3</sub> ISA, we focused on the detailed chapter from that previous document in identifying the at-risk factors and studies to review ((U.S. EPA 2013)). Factors with "adequate evidence" are genetic factors, asthma, children, older adults, diet, and outdoor workers. Factors with "suggestive evidence" are sex, SES, and obesity. Considering feasibility and our review criteria, we focused on studies addressing increased risks based on age in the adequate evidence group and note that some health functions already applied in the primary analysis focus on asthmatic subpopulations. We also elected to include illustrative calculations for some risk factors with "suggestive evidence", specifically those for sex.

#### 6.2.5.1 Study and Risk Estimate Identification Criteria for Populations At-Risk for O<sub>3</sub> Exposures

We compiled epidemiologic studies from the related section of Chapter 8 of the 2013 O<sub>3</sub> ISA for the following at-risk factors, excluding all other study types (e.g., toxicological studies), for a total of 28 studies ((U.S. EPA 2020)). This collection includes the following number of studies, with some studies duplicated for multiple endpoints.

- 9 studies for children,
- 10 studies for older adults, and
- 18 studies for sex

We excluded the genetic factors population from our analysis, as we do not currently have the capability to estimate health impacts among variant genotypes. We excluded diet, outdoor workers, and obesity for similar reasons, as we have no representative dataset for use in analysis with these risk factors. Effects on asthmatics were not included in this analysis because we currently lack highly resolved spatial data on asthma prevalence, in part because effects on asthmatic populations are included in the main analysis.<sup>84</sup> We also excluded the SES group as the studies associated with the SES group for O<sub>3</sub> were associated with other methodological challenges. We coded the identified studies into a spreadsheet and applied the initial screening criteria described previously. We collected information on mortality and/or morbidity endpoints assessed in each study and focused on all-cause mortality and respiratory morbidity endpoints. The remaining studies were evaluated based on the additional identification criteria described in Table 51.

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<sup>83</sup> Analyses of effect modification will not be included in the main analyses, so as to avoid the possibility of double-counting impacts. This potential uncertainty could also be described as the effect modification of individual risk factors.

<sup>84</sup> Effects on asthmatics using national level prevalence estimates are estimated in the main analysis.

Table 51. O<sub>3</sub> At-Risk Study Identification Criteria

Criteria	Description
Peer-Review	Peer-reviewed research exclusively
Study Design	Epidemiologic study
Ozone Study	Research on ozone exposure is used
Study Location	U.S. or Canada
Population Attributes	Presents risk estimates for clearly defined at-risk groups for which data currently exist in BenMAP-CE
Exposure Duration	Both short- and long-term exposure studies
Causal or Likely Causal Health Effects	Adequate or suggestive evidence for at-risk groups in ISA
Economically Valuable Health Effects	Health endpoints for which economic values have been or could reasonably be developed
Baseline Incidence Data	Must be able to identify baseline incidence data for subpopulations
Season	All year exposure or warm season exposure
Ozone Exposure Metrics	MDA8, or able to be converted to MDA8
Lag Structure	Choose model that most clearly represents the relationship between ozone exposure and the physiologic changes for the health endpoint

#### 6.2.5.2 Total Mortality

Regarding the health endpoint of mortality, three studies for older adults met our criteria: (Medina-Ramon and Schwartz 2008), (Zanobetti and Schwartz 2008), and (Katsouyanni, Samet et al. 2009). All three studies provided sufficient details to apply risk model information for short-term all-cause mortality among adult age groups.<sup>85</sup> There were no mortality studies for the child at-risk group in either the 2013 or 2020 O<sub>3</sub> ISAs ((U.S. EPA 2013, U.S. EPA 2020)). For the at-risk population stratified by sex, two studies met our initial criteria: (Medina-Ramon and Schwartz 2008), which evaluated short-term O<sub>3</sub> exposure and all-cause mortality, and (Jerrett, Burnett et al. 2009), which evaluated long-term O<sub>3</sub> exposure and respiratory mortality. Both studies provided sufficient data to apply risk model information to male and female subpopulations. We developed health impact functions for these studies.

The O<sub>3</sub>-mortality risk estimates for at-risk subpopulations reported in (Medina-Ramon and Schwartz 2008) required additional modification in order to use those results to develop health impact functions. The authors presented excess risk estimates for each subpopulation as the additional percent change in mortality for persons who have the condition, compared to persons without the condition. For our populations of interest, these subgroups were persons aged 65 or older compared to those younger than 65, and females relative to males. However, they did not report the risk estimate for these comparison groups, so in order to estimate the total excess risk for each exposed at-risk group, we needed to first back-calculate the excess risk for the comparison group without the factor of interest. We accomplished this by assuming that the authors' overall reported excess risk for the full sample of

<sup>85</sup> Calculations required to apply risk model information from Medina-Ramon, M. and J. Schwartz (2008). "Who is more vulnerable to die from ozone air pollution?" *Epidemiology*: 672-679. are described in the following paragraph.

0.65% (95% confidence interval = 0.38% to 0.93%) could be expressed as a weighted average of the unreported excess risk (“x”) and the full excess risk for the at-risk group, which would be expressed as the sum of x and the reported excess risk from (Medina-Ramon and Schwartz 2008) Table 2, where the weights are calculated using the total and at-risk group sample sizes in Table 1 of that paper. For example, to calculate the total excess risks for the females in the sample, we used the following equation:

$$ER_{Total} = \frac{ER_{Male}(Pop_{Male}) + ER_{Female}(Pop_{Female})}{Pop_{Total}}$$

where  $ER_{Total}$  is the full sample excess risk of 0.65%;  $ER_{Female}$  is the excess risk of ozone exposures for females;  $ER_{Male}$  is the excess risk of ozone exposures for males;  $Pop_{Total}$  is the total sample population; and  $Pop_{Female}$  and  $Pop_{Male}$  are the size of the female and male subsets of the sample population, respectively. We also know from Table 2 of that paper that:

$$ER_{Female} = ER_{Male} + 0.58 \%$$

Substituting and using the available information from (Medina-Ramon and Schwartz 2008) Tables 1 and 2, we can solve for  $ER_{Male}$  and then  $ER_{Female}$ :

$$0.65\% = \frac{ER_{Male}(1,365,937) + (0.58\% + ER_{Male})(1,363,703)}{2,729,640}$$

$$ER_{Male} = 0.36 \%$$

and

$$ER_{Female} = 0.36\% + 0.58\% = 0.94\%$$

We then used the full excess risk value for the female subpopulation to derive a health impact function for ozone-related mortality for females.

### 6.2.5.3 Respiratory Morbidity

We applied the same identification criteria described in section 6.2.5.1 to respiratory morbidity endpoints for the child and sex at-risk groups. Three studies for children met our criteria for inclusion: (Mar and Koenig 2009), (Paulu and Smith 2008), and (Villeneuve, Chen et al. 2007). Each study evaluated emergency room visits for asthma and provided sufficient risk model information stratified by age. No studies cited for the older adult population met our criteria for inclusion. Three studies for sex met our identification criteria: (Paulu and Smith 2008), (Cakmak, Dales et al. 2006), and (Lin, Stieb et al. 2005). These studies evaluated emergency room visits for asthma, all respiratory hospital admissions, and hospital admissions for lower respiratory infection, respectively. Each study provided sufficient risk model information for male and female subpopulations. We developed health impact functions for all studies identified above. All the at-risk studies we identified are summarized in Table 52.

Table 52. Identified O<sub>3</sub> At-Risk Beta Coefficients and Standard Errors

<b>At-Risk Factor</b>	<b>Endpoint</b>	<b>Study</b>	<b>Subgroup</b>	<b>Beta Coefficient (SE)<sup>1</sup></b>
Lifestage, older adults	Mortality, All Cause	(Medina-Ramon and Schwartz 2008) and (Zanobetti and Schwartz 2008)	Age 0-64	-0.0001 (0.0001)
			Age 65+	0.0010 (0.0002)
Lifestage, older adults	Mortality, All Cause	(Katsouyanni, Samet et al. 2009)	Age 0-74	0.0008 (0.0002)
			Age 75+	0.0007 (0.0003)
Lifestage, older adults	Mortality, All Cause	(Zanobetti and Schwartz 2008)	Age 0-20	0.0001 (0.0003)
			Age 21-30	0.0001 (0.0004)
			Age 31-40	0.0001 (0.0002)
			Age 41-50	0.0001 (0.0002)
			Age 51-60	0.0005 (0.0002)
			Age 61-70	0.0004 (0.0001)
			Age 71-80	0.0005 (0.0001)
			Age 81+	0.0003 (0.0001)
Sex	Mortality, All Cause	(Medina-Ramon and Schwartz 2008) and (Zanobetti and Schwartz 2008)	Female	0.0009 (0.0002)
			Male	0.0004 (0.00004)
Sex	Mortality, Respiratory	(Jerrett, Burnett et al. 2009)	Female	0.0044 (0.0011)
			Male	0.0011 (0.0014)
Lifestage, children	Emergency Room Visits, Asthma	(Mar and Koenig 2009)	Age 0-17	0.0104 (0.0044)
			Age 18+	0.0039 (0.0027)
Lifestage, children	Emergency Room Visits, Asthma	(Paulu and Smith 2008)	Age 2-14	0.0104 (0.0050)
			Age 15-34	0.0148 (0.0035)
Lifestage, children	Emergency Room Visits, Asthma	(Villeneuve, Chen et al. 2007)	Age 2-4	0.0032 (0.0033)

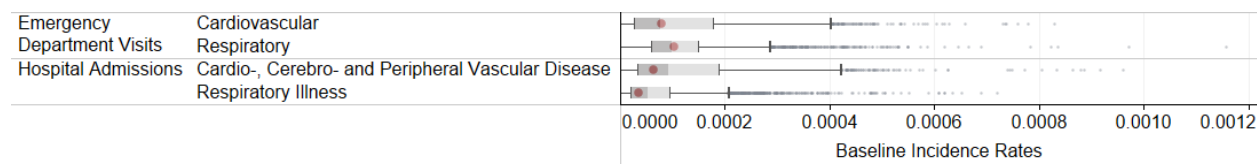
			Age 5-14	0.0073 (0.0024)
			Age 15-44	0.0058 (0.0018)
			Age 45-64	0.0063 (0.0033)
			Age 65-74	0.0073 (0.0055)
			Age 75+	-0.0006 (0.0067)
Sex	Emergency Room Visits, Asthma	(Paulu and Smith 2008)	Female	0.0113 (0.0027)
			Male	0.0104 (0.0032)
Sex	Hospital Admissions, All Respiratory	(Cakmak, Dales et al. 2006)	Female	0.0013 (0.0004)
			Male	0.0017 (0.0003)
Sex	Hospital Admissions, Lower Respiratory Infection	(Lin, Stieb et al. 2005)	Female	0.0087 (0.0060)
			Male	0.0040 (0.0052)

<sup>1</sup> Beta coefficients and SEs in this table have been converted to MDA8 for comparability

### 6.3 QUANTITATIVE CHARACTERIZATION OF BASELINE INCIDENCE RATE UNCERTAINTIES

When available from HCUP, we incorporate county-level hospital admissions and emergency department visit baseline incidence data. Comparisons of the county-level data (box and whisker plot) to the national-level data (red circles) are available in Figure 14.

Figure 14. Example County-Level (Distribution) and National-Level (Red Dot) Emergency Department Visit and Hospital Admission Baseline Incidence Data



We performed several quality assurance checks to ensure the incidence rates accurately reflect observed health outcomes in the underlying counties. These checks included:

- Examining data inputs to ensure the endpoints reflect the specified set of ICD codes from the epidemiological studies;
- Reviewing data processing scripts to ensure all calculations implement the intended procedures, as documented in the BenMAP-CE User Manual ((U.S. EPA 2018));
- Re-processing existing incidence rates in BenMAP-CE's "Other Incidence (2014)" to confirm that changes to data processing to incorporate new endpoints have no or minimal impact on incidence rate data for existing endpoints from BenMAP-CE's 2017 data update;

- Comparing the relative magnitude of related endpoints to ensure that incidence rates for broader endpoints (e.g., HA, All Respiratory) are greater than incidence rates for endpoints with a narrower set of ICD codes (e.g., HA, Asthma);
- Comparing national baseline incidence counts when using county-level incidence rates and nation-level incidence rates to ensure that, in aggregate, the two datasets produce similar results;<sup>86</sup> and
- Examining the geographic distribution of incidence rates to ensure no counties, states, or regions, are characterized by anomalously low or high incidence.

We identified no systematic errors or bias in the raw data or data processing steps. The main source of uncertainty in these data is related to imputation of rates where county data for specific endpoints were suppressed due to statistical reliability or privacy concerns. The state or regional rates used to substitute for these suppressed values may under- or over-estimate individual county rates.

## 6.4 QUANTITATIVE CHARACTERIZATION OF ECONOMIC VALUATION ESTIMATE UNCERTAINTIES

### 6.4.1 Mortality Cessation Lag

Following advice from the Health Effects Subcommittee of EPA's independent Science Advisory Board (SAB-HES), the agency typically assumes that some amount of time lapses between when air pollution is reduced and when PM-attributable mortality is reduced fully. Within the context of benefits analyses, this term is often referred to as "cessation lag." The duration of this lag affects how changes in PM-attributable mortality associated with long-term (i.e., years-long) exposure are valued. Economic theory suggests that the value of these future impacts should be discounted. The primary analysis included in recent RIAs assumes that this lag is distributed over a 20-year period, with 30% of deaths reduced in year 0, 50% occur in years 1-5, and the remaining 20% occur in years 6-20. This approach is generally supported by SAB recommendations ((Cameron 2001, Cameron 2004, Hammitt and Bailar 2010)).

Based on SAB requests and recommendations, we previously performed several quantitative uncertainty analyses with the goal of better understanding potential impacts of different cessation lag distribution assumptions ((U.S. EPA 2012)). Although it was determined that certain extreme lag structure assumptions may substantially impact monetized benefits, potentially increasing or decreasing monetized impacts by up to 25%, for most reasonable distributed lag model structures, differences in the specific shape of the lag function had relatively small impacts on overall PM<sub>2.5</sub> benefits estimates.

Newer evidence suggests the lag between exposure and the change in the risk of PM-attributable mortality may be shorter than the 20 years EPA now assumes. A long-term exposure cohort study performed by Crouse and colleagues of the CanCHEC evaluated the estimated hazard of non-accidental mortality according to three temporal moving averages (1, 3 and 8 years) ((Crouse, Erickson et al. 2020)). The authors found that "...longer moving averages resulted in stronger associations between PM<sub>2.5</sub> and mortality." An analysis of the Harvard Six Cities cohort observed that PM<sub>2.5</sub> concentrations observed in the year prior to mortality "...were the best fit exposure window for all-cause mortality" ((Lepeule, Laden et al. 2012)).

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<sup>86</sup> Aggregated county-level baseline incidence counts for all hospitalization and emergency department visit endpoints included in the main benefits estimates were within 10% of the national baseline incidence counts.

We do not know how long-term O<sub>3</sub> exposure-related respiratory deaths are distributed over time. Hence, when discounting the value of O<sub>3</sub>-attributable deaths we use two lag structures originally developed for PM<sub>2.5</sub> (the 20-year segmented lag used for PM<sub>2.5</sub> and an assumption of zero lag) as sensitivity analyses.

#### 6.4.2 Lung Cancer Cessation Lag

For a given health effect attributable to air pollution exposure, EPA reports the number of avoided cases associated with the estimated pollutant reduction in a specified year. However, for some health effects, there is an expected time lag between changes in pollutant exposure in a given year and the total realization of health effect benefits, commonly referred to in regulatory analyses as the “cessation lag” (section 6.4.1). For an outcome such as lung cancer, where the time between exposure and diagnosis can be quite long, it may take decades to realize the full benefits of the air quality improvements. Properly estimating the time course over which lung cancer health benefits are realized is critical for proper discounting of the economic value of these health benefits.

Following guidance from EPA’s Science Advisory Board ((Ostro 2004)), EPA RIAs have applied a 20-year distributed cessation lag model to estimate the temporal distribution of reductions in mortality risks, including fatal lung cancer cases. In the 20-year distributed lag model, 30 percent of the total mortality risk reductions occur in the first year following the exposure reduction, 50 percent are distributed evenly among years two through five, and the remaining 20 percent are distributed evenly among years six through 20. This structure reflects mortality risks from a variety of causes, with the mortality risk reductions occurring later representing mortality risks from lung cancer.

For non-fatal cancer incidence, we considered a similar cessation lag approach based on estimates of the lung cancer “latency period,” or the time that passes between exposure and diagnosis, when diseases processes may be occurring undetected and not yet resulting in observable symptoms. Based on findings in the 2019 PM ISA, EPA has recently developed a health impact function based on (Gharibvand, Shavlik et al. 2017) for non-fatal lung cancer incidence ((U.S. EPA 2019)). To support the new non-fatal lung cancer risk estimate, we applied an age-at-diagnosis cessation lag distribution for the main analysis as it accounts for age-specific latency period, instead of assuming a single latency duration. However, other potentially applicable distribution models are available that also take into account the latency between exposure and lung cancer diagnosis, such as the adapted 20-year distribution (section 6.4.2.1) and the latency-based triangular distribution (section 6.4.2.2). All potential lag cessation distributions, including the traditional 20-year lag distribution, are compared in section 6.4.2.3.

##### 6.4.2.1 Adapted 20-Year Distribution

We adapted the 20-year distributed lag model applied to VSL estimates in previous EPA RIAs using the estimated 10-year latency period. Following the latency period, the adapted 20-year model has zero cancer case reductions in years one through five and an even distribution of case reductions in years six through 20, resulting in scaling factors of 0.71 for a 3% discount rate or 0.46 for a 7% discount rate.

##### 6.4.2.2 Latency-Based Triangular Distribution

A continuous probability distribution shaped like a triangle may better assess lung cancer lag cessation. Triangular distribution based on a search of lung cancer latency periods from the peer-reviewed literature. Using the most common latency period of 10-years observed in the literature (Table 28), we



estimated a triangular distribution that spans from five to 20 years, with the peak of the distribution at ten years, the most common latency period estimate found in the literature (i.e., the mode). We identified a triangular distribution to reflect the uncertainty of latency period duration found in the literature, given the limited amount of information available to establish the shape and form of an uncertainty distribution. We used the cumulative probability function for this distribution to estimate the incremental annual number of cases likely to be diagnosed year to year by subtracting the cumulative probability from the previous year from the cumulative probability of the current year. We then used the resulting percentages to create a cessation lag model, allocating cases avoided in the years following an exposure change according to the corresponding yearly percentages.

#### 6.4.2.3 Comparison of Lung Cancer Lag Cessation Distribution Models

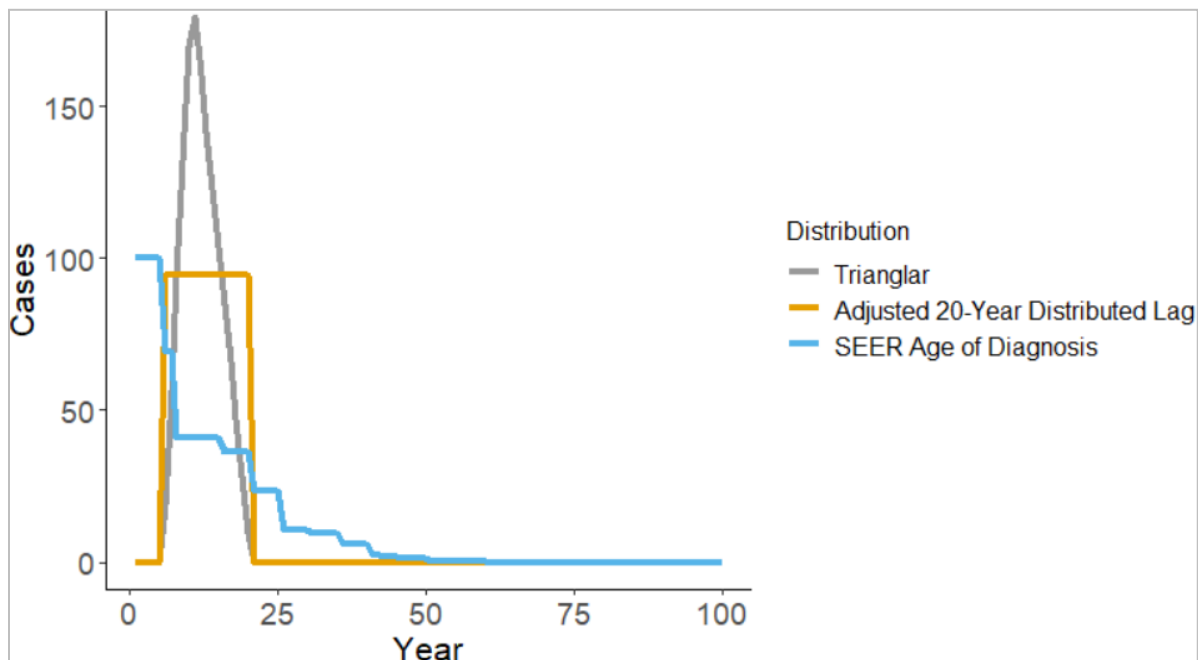
The effect of each potential cessation lag distribution model was converted into scaling factors (Table 53). The scaling factors of the adjusted 20-year lag distribution estimate falls between that of the traditional cessation lag and the triangular distribution lag estimates. Also, the adjusted cessation lag distribution underestimates as compared to the age-at-diagnosis distribution.

Table 53. Scaling Factors for Various Lung Cancer Lag Cessation Distribution Models

Discount Rate	Age Range	Scaling Factor	Lag Cessation Distribution Model
3%	65-99	0.668980939	Traditional VSL cessation lag, 3% DR
7%	65-99	0.398456232	Traditional VSL cessation lag, 7% DR
3%	30-99	0.70711338	Adjusted 20-Year Distributed Lag Adjustment Factor
7%	30-99	0.463225599	Adjusted 20-Year Distributed Lag Adjustment Factor
3%	30-99	0.72192703	Triangular Adjustment Factor
7%	30-99	0.480176715	Triangular Adjustment Factor
3%	30-34	0.350285148	SEER Age-Distribution Adjustment Factor
3%	35-44	0.427591186	SEER Age-Distribution Adjustment Factor
3%	45-54	0.553445022	SEER Age-Distribution Adjustment Factor
3%	55-64	0.675599356	SEER Age-Distribution Adjustment Factor
3%	65-74	0.775053763	SEER Age-Distribution Adjustment Factor
3%	75-84	0.843760064	SEER Age-Distribution Adjustment Factor
3%	85-99	0.916741635	SEER Age-Distribution Adjustment Factor
7%	30-34	0.108397669	SEER Age-Distribution Adjustment Factor
7%	35-44	0.168901798	SEER Age-Distribution Adjustment Factor
7%	45-54	0.294643444	SEER Age-Distribution Adjustment Factor
7%	55-64	0.445786107	SEER Age-Distribution Adjustment Factor
7%	65-74	0.590393871	SEER Age-Distribution Adjustment Factor
7%	75-84	0.702750875	SEER Age-Distribution Adjustment Factor
7%	85-99	0.82379138	SEER Age-Distribution Adjustment Factor

Using the lung cancer incidence risk estimates and a hypothetical scenario, we compared the three potential lung cancer cessation lag models. The annual reduction in cancer cases was estimated from zero to 100 years after the exposure change. For the triangular and adjusted 20-year distributed lag, all annual reductions occur within 20 years after exposure change and for the age of diagnosis distribution, all annual reductions fall within 67 years after exposure change (Figure 15) with 90% occurring by year 26.

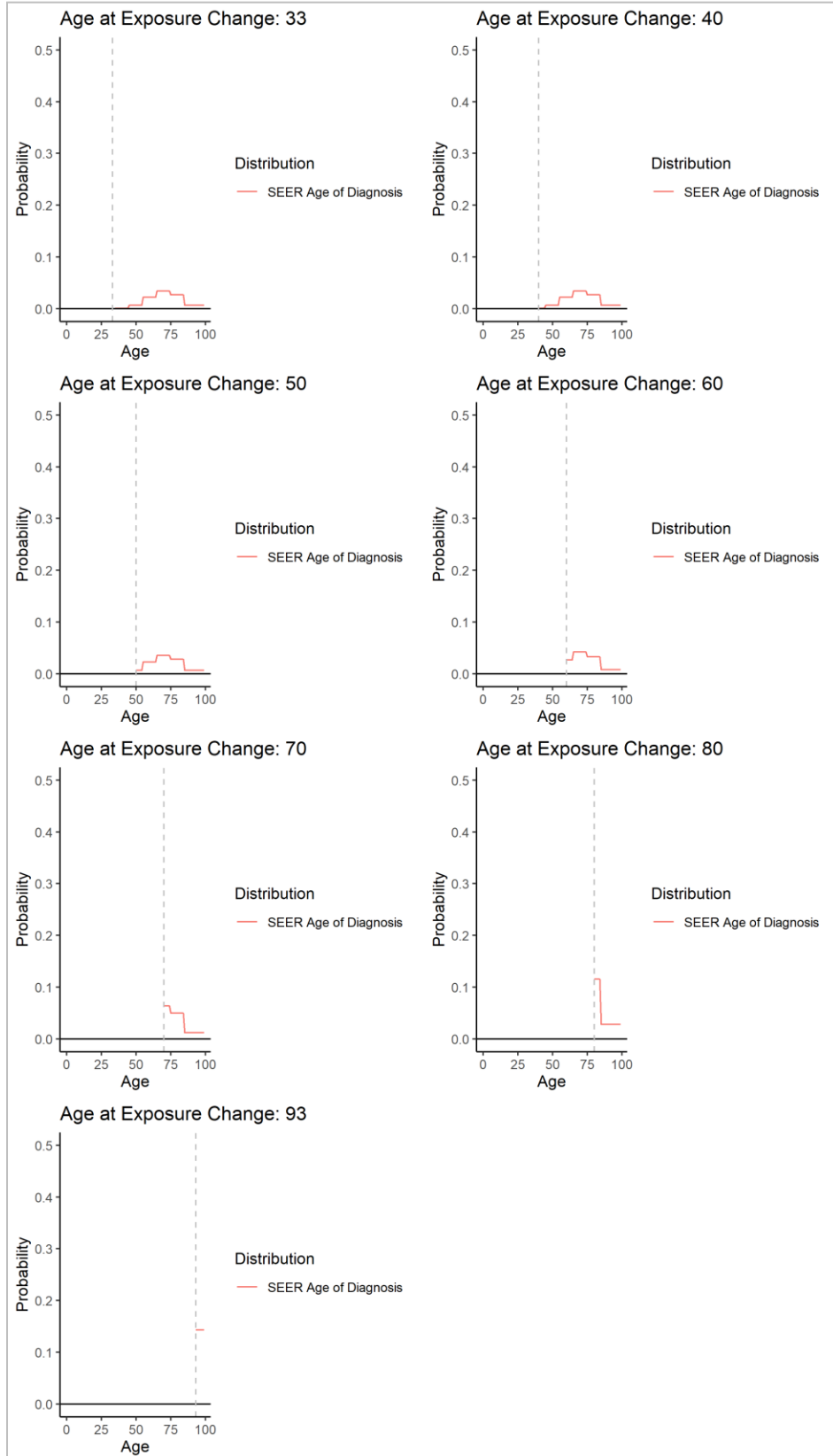
Figure 15. Lung Cancer Cases Cessation Lag Distribution by Model



A potential limitation of the triangular distribution and adjusted 20-year distributed lag is that the same latency period is used for all ages. For an exposure change experienced at 30, both the triangular distribution and adjusted 20-year distributed lag estimate that reductions occur between ages 35 and 50. However, SEER data indicates that less than 5% of lung and bronchus cancer diagnoses occur during this period. Conversely, for an exposure change experienced at 90, the reductions are realized from ages 95 to 110 (greater than life expectancy).

A limitation of the age-of-diagnosis distribution methods is that the highest reductions occur in the first five years for the age-of-diagnosis distribution and not all ages display latency periods (Figure 15). The factor used in this method estimates the time pattern of benefits based on the percentage of cancer incidence remaining in the life and results in older age bins without latency periods (Figure 16). While an age-dependent latency period may more accurately reflect the diagnosis data, the age-of-diagnosis distribution method may overestimate case reductions in earlier years by assuming all reduced cases for a change in exposure at later ages are realized by the end of life (age 99). At the same time, some cases are delayed by two to five decades, beyond latency values reported in the literature for lung cancer.

Figure 16. Lung Cancer Cases Reduction Distribution



### 6.4.3 Income Elasticity of Willingness to Pay

The degree to which one's WTP to reduce the risk of adverse effects changes in proportion to future changes in income is uncertain. We previously evaluated the potential impact of this factor on the monetized benefits in a sensitivity analysis ((U.S. EPA 2012)). Results are available below.

Our estimates of monetized benefits account for growth in real gross domestic product per capita by adjusting the WTP for individual endpoints based on the central estimate of the adjustment factor for each of the categories (minor health effects, severe and chronic health effects, mortality, and visibility). We previously examined how sensitive the estimate of total benefits is to alternative estimates of the income elasticities. Table 54 lists the ranges of elasticity values used to calculate the income adjustment factors, while Table 55 lists the ranges of corresponding adjustment factors. The results of this sensitivity analysis, giving the monetized benefit subtotals for the four benefit categories, are presented in Table 56.

Table 54. Ranges of Elasticity Values Used to Account for Projected Real Income Growth<sup>a</sup>

<b>Benefit Category</b>	<b>Lower Sensitivity Bound</b>	<b>Upper Sensitivity Bound</b>
Minor Health Effect	0.04	0.30
Mortality	0.08	1.00

<sup>a</sup>Derivation of these ranges can be found in (Kleckner and Neumann 1999). COI estimates are assigned an adjustment factor of 1.0.

Table 55. Ranges of Adjustment Factors Used to Account for Projected Real Income Growth<sup>a</sup>

<b>Benefit Category</b>	<b>Lower Sensitivity Bound</b>	<b>Upper Sensitivity Bound</b>
Minor Health Effect	1.018	1.147
Mortality	1.037	1.591

<sup>a</sup>Based on elasticity values reported in Table 54, U.S. Census population projections, and projections of real GDP per capita.

Table 56. Sensitivity of Monetized Benefits to Alternative Income Elasticities<sup>a</sup>

<b>Benefit Category</b>	<b>Benefits Incremental to Baseline (Millions of 2006\$)</b>	
	<b>Lower Sensitivity Bound</b>	<b>Upper Sensitivity Bound</b>
Minor Health Effect	\$30	\$31
Mortality <sup>b</sup>	\$3,600	\$3,800

<sup>a</sup>All estimates rounded to two significant digits.

<sup>b</sup>Using mortality effect estimate from (Krewski, Burnett et al. 2000) and 3% discount rate. Results using (Laden, Schwartz et al. 2006) or a 7% discount rate would show the same proportional range.

Consistent with the impact of mortality on total benefits, the adjustment factor for mortality has the largest impact on total benefits. The value of mortality in 2020 ranges from 96% to 108% of the main estimate based on the lower and upper sensitivity bounds on the income adjustment factor. The effect on the value of minor health effects is much less pronounced, ranging from 86% to 133% of the main estimate for minor effects.

#### 6.4.4 Statistical Estimates of VSL

EPA relies on published peer-reviewed studies to provide statistical estimates of the value of avoided statistical mortality risk (VSL). These studies provide a range of different estimates due to varying study design and different statistical samples. EPA uses a distribution of values fit to the studies' estimates as described in Section 5.1.1 and Table 22.

#### 6.4.5 Alzheimer's Disease and Parkinson's Disease Onset Lifetime Costs

The epidemiologic study from which the risk estimates for Alzheimer's and Parkinson's disease were identified used time to first hospital admission as the health endpoint readout. As the authors note that this is not necessarily indicative of disease onset, we only include valuation estimates of associated hospital admissions costs in the main benefits assessment. However, we include information here regarding how the benefits estimates would increase if the first hospital admission were used as a surrogate for disease onset.<sup>87</sup>

##### 6.4.5.1 Alzheimer's Disease

Potential valuation sources of Alzheimer's disease lifetime medical costs were available from the (Alzheimer's 2020) report and (Jutkowitz, Kane et al. 2017). Using (Alzheimer's 2020), we first developed an estimate of incremental annual medical expenses for Medicare beneficiaries living with Alzheimer's Disease (Table 57). Then, using the estimated life expectancy duration of 5 year from (Jutkowitz, Kane et al. 2017), 3% and 7% discounted costs were extrapolated (Table 58). We note that the average/median age of Alzheimer's disease diagnosis/onset is after the age of 65, at which we assume retirement, so any potential lost wages are not included in this valuation estimate. Lifetime medical costs, excluding hospitalization, are estimated at \$156,920 using a 3% discount rate or \$145,946 using a 7% discount rate in 2015\$ (Alzheimer's 2020).

Table 57. Annual Alzheimer's Disease Valuation Estimate Calculation

Service	Beneficiaries with Alzheimer's Disease or Other Dementia	Beneficiaries without Alzheimer's Disease or Other Dementia
Inpatient hospital	\$11,465	\$3,703
Medical provider	\$5,762	\$3,589
Skilled nursing facility	\$7,213	\$493
Nursing home	\$16,523	\$800
Hospice	\$2,126	\$161
Home health care	\$2,661	\$386
Prescription Medications	\$3,481	\$2,986
Annual Medical Expenses (\$2019)	\$49,231	\$12,118
Annual Medical Expenses (\$2015)	\$44,128	\$10,862
<b>Incremental Annual Medical Expenses for Medicare beneficiaries with AD (\$2015)</b>	<b>\$33,266</b>	

<sup>87</sup> Baseline incidence and prevalence data would need to be updated to estimate impacts of disease onset.

Table 58. Lifetime Alzheimer’s Disease Valuation Estimate Calculation (2015\$)

Year	3% Discount Rate	7% Discount Rate
0	\$33,266	\$33,266
1	\$32,297	\$31,090
2	\$31,357	\$29,056
3	\$30,443	\$27,155
4	\$29,557	\$25,379
<b>Total Lifetime Costs</b>	<b>\$156,920</b>	<b>\$145,946</b>

(Jutkowitz, Kane et al. 2017) provided information needed to separately develop a lifetime Alzheimer’s Disease cost estimate with a 3% discount rate, but not with a 7% discount rate (Table 59. Additional Lifetime Alzheimer’s Disease Valuation Estimate Calculation with a 3% Discount Rate (2015\$)). As the 3% discount rate estimate of \$156,920 from (Alzheimer’s 2020) is fairly similar to the lifetime 3% discount rate estimate of \$184,500 from (Jutkowitz, Kane et al. 2017), we have additional confidence in the validity of the (Alzheimer’s 2020) estimates (Table 21).

Table 59. Additional Lifetime Alzheimer’s Disease Valuation Estimate Calculation with a 3% Discount Rate (2015\$)

Service	Base-Case (83-year-old incident dementia case)	Counterfactual Dementia Free	Incremental Increase in Lifetime Costs
Value of informal caregiving	\$135,300	\$2,460	\$132,840
Out-of-pocket expenditures	\$89,840	\$64,720	\$25,120
Medicaid expenditures	\$44,090	\$37,450	\$6,640
Medicare expenditures	\$52,540	\$32,650	\$19,890
<b>Total value</b>	<b>\$321,780</b>	<b>\$137,280</b>	<b>\$184,500</b>

#### 6.4.5.2 Parkinson’s Disease

(Yang, Hamilton et al. 2020) provided estimates of lifetime costs, including direct, indirect, and non-medical costs. Using (Yang, Hamilton et al. 2020), we first developed an annual estimate of excess costs associated with living with Parkinson’s Disease for one year (Table 60). Then, using the estimated life expectancy duration of 14.6 years from (De Pablo-Fernandez, Tur et al. 2017), the 3% and 7% discounted costs were extrapolated (Table 61). Lifetime medical costs are estimated at \$567,285 using a 3% discount rate or \$445,792 using a 7% discount rate in 2015\$ (Table 21).

Table 60. Annual Parkinson’s Disease Valuation Estimate Calculation

<b>Service</b>	<b>Excess Cost per Person with Parkinson’s Disease</b>	<b>Description</b>
<i>Direct Medical Costs</i>		
Non-acute institutional care	\$6,888	Quantify excess healthcare cost of each person with Parkinson’s Disease compared with 10 matched individuals without Parkinson’s Disease
Hospital inpatient	\$6,932	
Outpatient	\$5,308	
Physician office	\$1,182	
Durable medical equipment	\$140	
Prescription medication	\$3,988	
<i>Direct Medical Costs Subtotal</i>	<i>\$24,438</i>	
<i>Indirect Medical Costs</i>		
Paid daily non-medical care	\$3,709	Home caretakes/long-term care facilities
Home modification	\$2,151	
Motor vehicle modification	\$897	
Other expenses	\$508	
<i>Indirect Medical Costs Subtotal</i>	<i>\$7,265</i>	
<i>Non-Medical Costs</i>		
Reduced employment	\$2,579	Reduced labor market participation due to early retirement
Absenteeism	\$4,869	Lost work days
Presenteeism	\$2,841	Lost work productivity at work
Social productivity loss in volunteer work	\$997	
Supplemental security income (SSI)	\$541	SS disability supplemental income
Social security disability insurance (SSDI)	\$1,617	
Other disability income	\$2,431	Includes other disability income sources such as VA disability, gov't employee disability, & state disability insurance or personal disability insurance payments
<i>Non-Medical Costs Subtotal</i>	<i>\$18,293</i>	
Annual Medical Expenses (\$2017)	\$47,578	
<b>Annual Medical Expenses (\$2015)</b>	<b>\$44,718</b>	

Table 61. Lifetime Parkinson’s Disease Valuation Estimate Calculation

<b>Year</b>	<b>3% Discount Rate</b>	<b>7% Discount Rate</b>
0	\$44,718	\$44,718
1	\$43,416	\$41,793
2	\$42,151	\$39,059
3	\$40,924	\$36,503
4	\$39,732	\$34,115
5	\$38,574	\$31,883
6	\$37,451	\$29,798
7	\$36,360	\$27,848
8	\$35,301	\$26,026
9	\$34,273	\$24,324
10	\$33,275	\$22,732
11	\$32,305	\$21,245
12	\$31,364	\$19,855
13	\$30,451	\$18,556
14	\$29,564	\$17,343
14.6	\$17,427	\$9,992
<i>Total Lifetime Costs (14.6 yr survival)</i>	<i>\$567,285</i>	<i>\$445,792</i>

## 6.5 QUALITATIVE CHARACTERIZATION OF UNCERTAINTIES

There are several uncertainties we are unable to fully or partially quantitatively assess, but qualitatively discuss below, in alphabetical order.

### 6.5.1 Applying Risk Estimates to Locations and Populations not Specified in the Epidemiologic Study

EPA regulatory actions often affect portions of the country and populations that differ from those considered in the epidemiologic studies providing the risk estimates. EPA commonly transfers risk estimates from one location or population to another, following a procedure called benefits transfer, a potential source of uncertainty. When available, risk estimates based on nationwide studies reflecting the overall population demographics of U.S. residents will be used when estimating health benefits. Epidemiologic studies exploring the relationship between air pollution and the risk of mortality often consider populations whose characteristics are broadly representative of the U.S. (e.g., Medicare-based estimates will be applied to those >64). By contrast, epidemiologic studies examining morbidity outcomes may focus on population subsets, such as those residing in specific geographic regions, a single sex, or selected races/ethnicities. In this context, two or more epidemiologic studies may report risk estimates that, when pooled, can better characterize risks experienced by U.S. populations. However, in some cases it may be scientifically inappropriate to pool risk estimates—for example, a nationwide analysis of populations ages 65-99 and a less-geographically diverse analysis of populations ages 0-99. In a situation such as this, the estimate best characterizing risk in the U.S. will be included in the main benefits assessment and the others will be included in quantitative sensitivity analyses (sections 6.1 and 6.1.6).



### 6.5.2 Causality Determination

When estimating air pollutant-attributable health impacts, EPA focuses on endpoints for which the underlying scientific evidence is strongest. This approach is based on evaluating evidence across scientific disciplines (i.e., clinical, animal toxicological, and epidemiologic) with regard to consistency of effects within a discipline, coherence of effects across disciplines, and evidence of biological plausibility. Such an approach gives us greater confidence in the relationship between exposure and health outcome. For criteria pollutants, EPA typically relies upon the causality determinations in the latest ISA or equivalent, which are made using a weight-of-evidence approach. These causality determinations are, however, made for categories of health effects and not for specific endpoints. Thus, the extent to which the relationship exists for the specific endpoint and the exposure circumstances of interest in a benefits assessment is a source of uncertainty.

An expert elicitation sponsored by EPA to characterize the uncertainty in the relationship between PM<sub>2.5</sub> and mortality, including causal uncertainty, was released in 2006 and reviewed by the Advisory Council on Clean Air Compliance ((IEc 2006, Hammitt 2008)). Although the 12 expert-defined concentration-response functions provide useful information on the sensitivity of the health benefits estimates, additional epidemiology literature which addresses some of the weaknesses identified by the expert elicitation has since become available, such as improved exposure estimation techniques and the use of cohorts more representative of the U.S population. For these reasons we do not include the expert-derived results as a sensitivity analysis here but consider it as qualitative support for the relationship between long-term PM<sub>2.5</sub> exposures and all-cause mortality impacts.

Causal inference is another method of establishing a causal connection that evaluates associations under changing conditions. The 2019 PM ISA stated that “overall, the results of these causal inference studies contribute to the body of epidemiologic evidence that informs the causal relationship between long-term (one month to years) PM<sub>2.5</sub> exposure and total mortality ((U.S. EPA 2019)). Observing consistent results for this relationship across studies using different analytic techniques (i.e., difference-in-difference approach) increases our confidence in the relationship.”

### 6.5.3 Estimating and Assigning Exposures in Epidemiology Studies

New developments in exposure assessment, including hybrid spatiotemporal models that incorporate satellite observations of aerial optical density, land use variables, surface monitoring data from monitors, and chemical transport models, have led to improvements in pollutant concentration estimates. After reviewing the current state of exposure science, the 2019 PM ISA stated that “a number of studies demonstrate that the positive associations observed between long-term PM<sub>2.5</sub> exposure and mortality are robust to different methods of assigning exposure” and the 2020 O<sub>3</sub> ISA articulated that “hybrid methods have produced lower error predictions of ozone concentration compared with spatiotemporal models using land use and other geospatial data alone but may be subject to overfitting given the many different sources of data incorporated into the hybrid framework” ((U.S. EPA 2013, U.S. EPA 2019)).

Although these advancements may reduce bias and uncertainty in risk estimates, the accuracy of hybrid exposure estimates is difficult to confirm in areas lacking monitors. On the other hand, studies using monitor data as the only exposure information have increasing exposure uncertainty the farther people live from the monitor site.

Uncertainties related to PM<sub>2.5</sub> and O<sub>3</sub> exposure estimation vary. For example, the PM<sub>2.5</sub> HBM method had Pearson *R*'s ranging from 0.91 to 0.94 when applied across the U.S. at a 36-km resolution, depending on the geoimputation approach of the CMAQ data ((U.S. EPA 2019)). Evaluation of the O<sub>3</sub> HBM method has been relatively limited. However, overall conclusions regarding long-term O<sub>3</sub> exposure estimates that include fixed-site monitor measurements are that “the true effect of long-term exposure to ambient ozone may be underestimated or overestimated by the model” and that it “is much more common for the effect estimate to be underestimated, and the bias is typically small in magnitude” ((U.S. EPA 2020)).

#### 6.5.4 Modeling the Influence of Air Pollution on the Risk of Mortality Over Time

Air pollution benefits assessments commonly use a “pulse” approach, wherein counts of premature deaths and illnesses are attributed to air quality changes in a single year. To the extent that simulated changes in air quality persist over time—that is, concentrations are reduced over a multi-year period—then the pulse method may under-estimate the cumulative impact of air pollution on health ((Roman, Neumann et al. 2022)). Partly for this reason, researchers have employed a “dynamic” approach to estimating multi-year changes in air pollution risk using a life table (Miller and Hurley 2003). A life table estimates the air pollution-attributable risk for each individual in a specified cohort on a year-to-year basis. When estimating the risk of premature death, the probability of dying in each year is conditional upon having lived to that year. Noting the advantages of this approach compared to the pulse method, the U.S. EPA Science Advisory Board noted that life tables “...provide the most realistic available modeling how, over time, changes in population risk led to changes in the size and age distribution of the population, with consequent implications for estimated mortality impacts” ((Hammit and Bailar 2010)).

EPA’s PopSim tool, which builds upon the World Health Organization (WHO) LIFET tool, estimates changes in life expectancy at birth, life years and counts of attributable deaths ((Miller and Hurley 2003)). In contrast with the BenMAP-CE tool, PopSim quantifies these effects at a national scale and thus (in its current form) is unable to estimate spatially resolved effects; it is also not designed to quantify morbidity effects and does not yet include baseline death rates stratified by race or ethnicity. Hence, the tool is a complement, rather than a substitute, for BenMAP-CE.

#### 6.5.5 Differential Toxicity of PM<sub>2.5</sub> According to Chemical Composition

PM<sub>2.5</sub> is a heterogenous mixture of solid and liquid particles suspended in air and can vary with regards to size, composition, and source. The 2019 PM ISA found that “across exposure durations and health effects categories...many PM<sub>2.5</sub> components and sources are associated with many health effects, and the evidence does not indicate that any one source or component is consistently more strongly related to health effects than PM<sub>2.5</sub> mass;” although, it was also noted that “most studies that examine PM sources and components focused on PM<sub>2.5</sub>” ((U.S. EPA 2019)).

Since the 2019 PM ISA concluded that “recent studies continue to demonstrate that no individual PM<sub>2.5</sub> component or source is a better predictor of mortality than PM<sub>2.5</sub> mass” and “many PM<sub>2.5</sub> components and sources are associated with many health effects and that the evidence does not indicate that any one source or component is consistently more strongly related with health effects than PM<sub>2.5</sub> mass” we continue to assume that all fine particles, regardless of their chemical composition, are equally potent in causing mortality and do not quantitatively assess uncertainties related to potential differences in PM<sub>2.5</sub>

toxicity or composition. A qualitative discussion of this uncertainty as it relates to respiratory effects, cardiovascular effects, and mortality can be found in section 1.5.4 of the 2019 PM ISA ((U.S. EPA 2019)).

#### 6.5.6 Different Long-Term Exposure Windows

The delay between changes in exposure and changes in health is an empirical challenge in estimating potential health effects associated with air pollution exposure. For example, if health impacts of high pollutant exposures have a long latency, risk estimates attributing to lower pollutant concentrations experienced more recently may be biased away from the null. However, the 2019 PM ISA states that “new evidence from recent studies continues to support the previous conclusion that health benefits from reducing air pollution could be expected with a few years of intervention” ((U.S. EPA 2019)). This issue is likely less relevant to O<sub>3</sub> exposure-attributable mortality, as those studies often have very similar, if not overlapping, health and air quality data.

#### 6.5.7 Discounting Future Benefit Estimates

Discounting reflects that people prefer benefits presently more than in the future. When appropriately applied, discounting can allow for the direct comparison of future benefits to costs. However, there are potential uncertainties associated with discounting future benefit estimates. EPA bounds discounted benefits and costs using an estimate of the consumption rate of interest and a rate of return on private capital given that the share of capital that is displaced by a regulation is unknown. OMB currently recommends, and EPA uses, a real consumption rate of discount of 3% and a real rate of 7% for the opportunity cost of private capital based on prior empirical estimates ((OMB 2003)). These values are estimates and therefore introduce uncertainty. Additional detail on discounting can be found in the EPA *Guidelines for Preparing Economic Analyses* ((U.S. EPA 2014)).

#### 6.5.8 Statistical Estimates of WTP

EPA relies on published peer-reviewed studies to provide statistical estimates of the value of avoided pain and suffering (WTP). While most of these studies provide estimates of the uncertainty due to statistical sampling, there are other important sources of error. First, the statistical models used to produce these estimates may be incorrect, termed modeling error. Second, the statistical samples used to produce these estimates may be selectively chosen and unlike the population of interest, leading to selection error. Third, WTP values are unavailable for many health endpoints of interest. Assigning a value of zero is clearly incorrect, but the EPA has no basis on which to assign other values.

#### 6.5.9 Confounding by Individual Risk Factors

Interindividual variability in both physiological responses and exposures to ambient air pollution can affect the size of reported risk estimates in epidemiologic studies. Well-designed epidemiology studies account for individual risk factors as covariates in their models<sup>88</sup>, and so all else being equal we identify risk estimates adjusted to control for the most covariates that could reasonably impact the risk estimate. However, confounding by individual risk factors remains a potential source of uncertainty as additional relevant covariates may exist that are not included as covariates in epidemiological risk estimates used for health benefits assessment. Unfortunately, we are currently unable to quantitatively assess this area of uncertainty but will include qualitative discussions when possible.

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<sup>88</sup> Common covariates include education level, marital status, body mass index, cigarette smoking, diet, occupational exposures, income, percentage of minority, unemployment, and poverty.

#### 6.5.10 Confounding by Other Pollutants

When considering the relationship between pollutant exposure and health impacts, it can be informative to consider whether risk estimates are changed when other pollutants are included in copollutant models, especially when health impacts of multiple pollutants are being estimated concurrently. Regarding long-term exposures, the 2019 PM ISA concluded that “positive associations observed between long-term PM<sub>2.5</sub> exposure and total mortality remain relatively unchanged after adjustment for...NO<sub>2</sub> and PM<sub>10-2.5</sub>” and the 2020 O<sub>3</sub> ISA found that “positive associations observed between long term O<sub>3</sub> exposure and total mortality remain relatively unchanged after adjustment for...NO<sub>2</sub>.” However, confounding due to the effects of copollutants other than O<sub>3</sub> and PM<sub>2.5</sub> are a potential source of uncertainty.

#### 6.5.11 Risk Attributable to Long-Term and Short-Term Exposures

Long- and short-term exposures may follow similar or divergent biological pathways. When pathways are similar, estimates of impacts from long-term exposures may include short-term impacts and vice-versa. However, if pathways diverge, long- and short-term impacts may be the sum, or even greater than the sum, of the two exposure durations. As there is little research directly comparing long- and short-term effects, we are currently unable to quantitatively assess this area of uncertainty for either PM<sub>2.5</sub>- or O<sub>3</sub>-attributable health effects.

#### 6.5.12 Heterogeneity of Risk Estimates

Epidemiologic studies often differ according to study design, geographic locations, age groups, population attributes, study size, methods for estimating exposure, range of pollutant concentrations, time periods, study sizes, and follow-up durations. These differences in turn influence the magnitude and standard error of study-reported risk estimates. The diversity of identified risk estimates could reflect either the variability across the populations studied or uncertainty around the risk estimates. Importantly, heterogeneous risk estimates are not necessarily indicative of bias, but could also result from variability of the underlying input parameters.

#### 6.5.13 O<sub>3</sub> Metrics<sup>89</sup>

O<sub>3</sub> exposure metrics used to develop risk estimates can take many forms, though the most widely used metrics are the maximum daily 8-hour average (MDA8), daily average 24-hour (DA24), daily average 8-hr from 10AM to 6PM (DA8), and maximum daily 1-hour average (MDA1) metrics.

Historically, if epidemiologic studies developed risk estimates based on O<sub>3</sub> metrics other than MDA8, EPA would adapt the risk estimates based on average conversion ratios to be appropriate for use with air quality surfaces projected in the MDA8 metric ((Anderson and Bell 2010)). This approach brings with it uncertainties associated with the simplifying assumptions used to develop the conversion ratios. In most cases, the day-to-day variation in different metrics (e.g., DA24 vs MDA8) is highly correlated. As such, the relationships between health impacts and different ozone metrics will also be highly correlated. However, when we apply risk estimates derived from time series results to evaluate the impacts of a specific policy scenario, we focus most on the shift in the overall distribution of O<sub>3</sub> concentrations over an entire season, instead of on the day-to-day variation in O<sub>3</sub> levels. Because

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<sup>89</sup> PM<sub>2.5</sub> exposure metrics are not discussed here as the vast majority are based on daily 24-hour average concentrations and annual exposures are often estimated using daily 24-hour average concentrations. Importantly, this potential source of uncertainty is not likely to have a large effect on overall PM<sub>2.5</sub> benefits estimates results.

specific policy scenarios might result in different temporal distributions of ozone concentrations than was observed in the monitored ozone data used in the studies, it is important to choose an O<sub>3</sub> metric that is best suited to capturing changes in O<sub>3</sub> that are likely to occur during hours where populations are likely to be exposed.

#### *6.5.13.1 Converting O<sub>3</sub> Risk Estimate Exposure Metrics*

When epidemiologic risk estimates are developed using non-MDA8 O<sub>3</sub> exposure metrics, EPA has typically converted the beta risk estimates into MDA8 metrics, which brings in a potential source of uncertainty ((Anderson and Bell 2010)). We discuss uncertainties associated with converting various common O<sub>3</sub> exposure metrics into the MDA8 metric below.

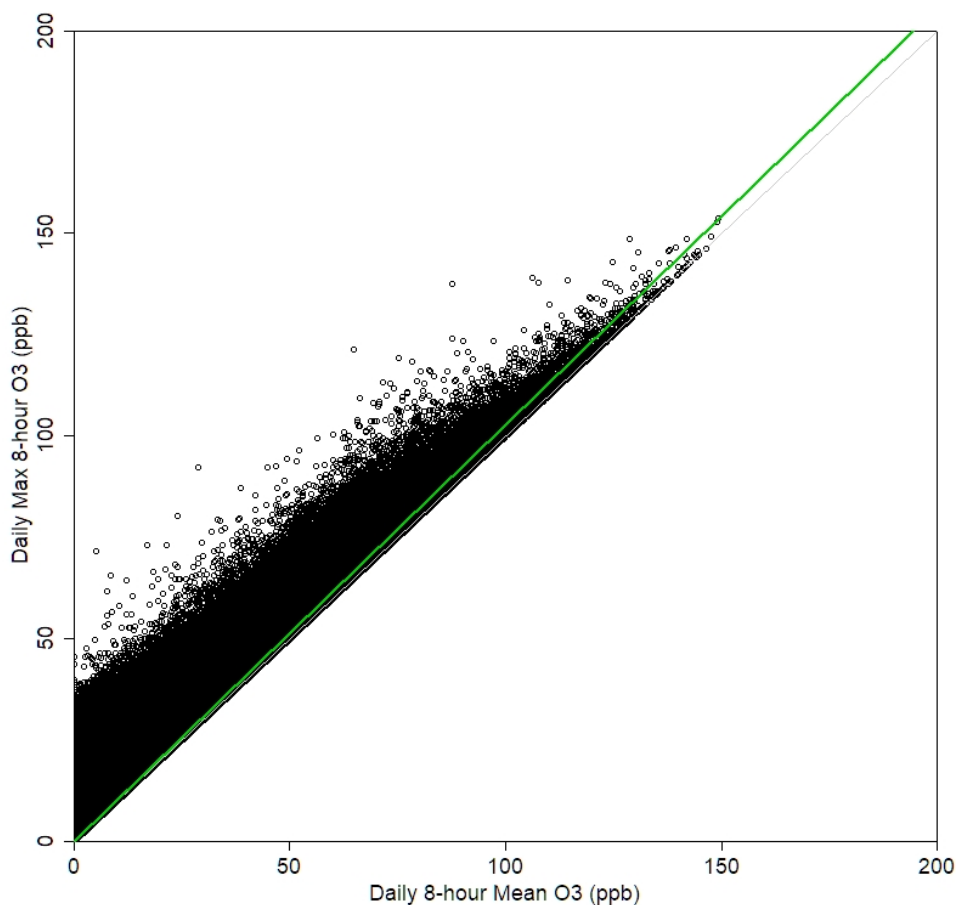
##### 6.5.13.1.1 DA24 to MDA8

Currently, air quality projections using the DA24 metric are unavailable, so a conversion factor from (Anderson and Bell 2010) is used in order to apply these risk estimates to MDA8 air quality surface projections. We multiply the beta risk estimate by the inverse of the median summer ratio of MDA8 to DA24 mean O<sub>3</sub> concentrations (i.e.,  $1 / 1.53 = 0.6536$ ) for studies assessing summer O<sub>3</sub> exposure or by the inverse of the fixed effects average ratio of MDA8 to DA24 mean O<sub>3</sub> concentrations (i.e.,  $1 / 1.53 = 0.6536$ ) for studies assessing all-year O<sub>3</sub> exposure. We note that (Anderson and Bell 2010) included a range of ratios from 1.23-1.83.

##### 6.5.13.1.2 DA8 to MDA8

A comparison of the MDA8 and DA8 metrics using 20 years of O<sub>3</sub> monitoring data (2000-2019) for the entire contiguous U.S. resulted in a very high rate of correlation (Figure 17). The correlation was based on a simple linear regression with zero intercept, meaning that if the MDA8 is 0, then the DA8 mean must also be zero. The green line denotes the regression line and the light gray line represents a 1:1 relationship. Please note, the MDA8 cannot exceed the DA8 and the high density of the ~7 million points shown in the graph cluster near the 1:1 line. In fact, the MDA8 and DA8 metrics are identical approximately 30% of the time and differ by 2 ppb or less about 80% of the time. Based on this comparison, the conversion factor from DA8 to MDA8 is 0.97.

Figure 17. Correlation of MDA8 and DA8 O<sub>3</sub> Exposures Between 2000-2019 (R=0.986)



#### 6.5.13.1.3 MDA1 to MDA8

Due to time and resource limitations, air quality projections using the MDA1 metric are also unavailable for the Proposed Reconsideration of the PM NAAQS rulemaking, so a conversion factor from (Anderson and Bell 2010) is used in order to apply these risk estimates to MDA8 air quality surface projections. We multiply the beta risk estimate by the median summer ratio of MDA1 to MDA8 O<sub>3</sub> concentrations (i.e., 1.13) for studies assessing summer O<sub>3</sub> exposure or by the fixed effects average ratio of MDA1 to MDA8 O<sub>3</sub> concentrations (i.e., 1.14) for studies assessing all-year O<sub>3</sub> exposure. We note that (Anderson and Bell 2010) included a range of ratios from 1.08-1.26.

#### 6.5.14 O<sub>3</sub> Season

Studies of O<sub>3</sub> vary with regards to O<sub>3</sub> season, limiting analyses to various definitions of summer (e.g., April-September, May-September or June-August) and exposures over the full calendar year. These differences can reflect state-specific, EPA-defined O<sub>3</sub> seasons or another seasonal definition chosen by the study author. O<sub>3</sub> exposure estimates are arguably more accurate during the summer when concentrations are typically higher and more monitors are operational. In addition, respiratory effects associated with short-term exposures are commonly limited to the warm season and therefore reflect the incidence that occurs during the 5- or 6-month O<sub>3</sub> season ((U.S. EPA 2020)). Recently, there are an

increased number of long-term analyses of O<sub>3</sub>-attributable health impacts over the full calendar year using hybrid modeling techniques and where O<sub>3</sub> monitoring data is collected for the entire year. These studies likely represent a more complete estimate of O<sub>3</sub>-attributable health impacts.

While epidemiologic studies assessing all-year O<sub>3</sub> exposures would likely present more comprehensive estimates of health impacts, hybrid O<sub>3</sub> surface projections for baseline and policy rulemaking scenarios are not currently available.<sup>90</sup> As such, we identified epidemiologic studies and associated risk estimates that evaluated associations between exposures and warm season effects when available. There was some variability amongst the warm season definitions within the list of studies identified in this update (e.g., April-September and June-August), although only the respiratory emergency department and asthma symptom risk estimate was based on full year O<sub>3</sub> exposures ((Lewis, Robins et al. 2013, Barry, Klein et al. 2019)). It should be noted that the exposures for asthma symptoms among the identified studies were not evenly distributed across all the seasons (i.e., three in Spring, two in Summer, two in Fall, and one in Winter).<sup>91</sup>

There is some variability regarding the definition of the warm season amongst epidemiologic studies included in the ISAs and the main risk estimates identified here for O<sub>3</sub> benefits estimates. When there is a substantial difference, such as the June-August warm season assessed by (Zanobetti and Schwartz 2008), we develop season-specific air quality projections, when feasible. However, many studies begin the 5-7 month warm season in either April or May and conclude the season in September or October. Since projected full year hybrid O<sub>3</sub> surfaces are currently not available, epidemiologic risk estimates will be applied to the air quality projection most closely matching the exposure season in the study (e.g., April-September exposures will be applied to May-September air quality projections). We expect this seasonal mismatch will only have a limited effect on the magnitude of related health incidence.

#### 6.5.15 Shape of the Concentration-Response Relationship

##### 6.5.15.1 PM<sub>2.5</sub>

An important consideration when characterizing uncertainty is whether the concentration-response relationship is linear across the full concentration range that is encountered, or if there are concentration ranges where there are departures from linearity. Overall, evidence from the 2019 PM ISA continues to “support a linear, no-threshold concentration-response relationship for long-term exposure to PM<sub>2.5</sub> and total (nonaccidental) mortality, especially at lower ambient PM<sub>2.5</sub> concentrations, with confidence in some studies in the range of 5–8 µg/m<sup>3</sup>” and “there is less certainty in the shape of the concentration-response curve at mean annual PM<sub>2.5</sub> concentrations generally below 8 µg/m<sup>3</sup>, although some studies characterize the concentration-response relationship with certainty down to 4 µg/m<sup>3</sup>” ((U.S. EPA 2019)).

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<sup>90</sup> The paucity of O<sub>3</sub> monitoring data in winter months potentially complicates the development of full year projected O<sub>3</sub> surfaces, which would need to be subject to comprehensive evaluation prior to use in EPA RIAs.

<sup>91</sup> When risk estimates based on full-year, long-term O<sub>3</sub> exposures are applied to warm season air quality projections, the resulting benefits assessment may underestimate impacts, due to a shorter timespan for impacts to accrue. When risk estimates based on full-year, short-term O<sub>3</sub> exposures are applied to warm season air quality projections, the resulting benefits assessment may also underestimate impacts, as short-term O<sub>3</sub> exposure effects are typically larger during the warm season (U.S. EPA (2020). Integrated Science Assessment for Ozone and Related Photochemical Oxidants (Final Report). O. o. R. a. Development. Washington, DC, U.S. Environmental Protection Agency.).

Although ten large cohort studies of long-term PM<sub>2.5</sub>-attributable mortality observed linear, no-threshold concentration-response relationships, three Canadian studies presented evidence of deviations from linearity down to the lowest concentration evaluated. Two studies found evidence of a supralinear relationship at lower concentrations, although only one was statistically significant. And a single study found that the best fit for the long-term PM<sub>2.5</sub> mortality relationship was in a threshold model with a threshold at 11 µg/m<sup>3</sup>.

There are several potential explanations for these results, one of which is that studies may be unable to adequately evaluate the relationship at low levels without sufficient population exposure at those levels. Consistent with that hypothesis, the single statistically significant study finding evidence of supralinearity did have one of the lowest mean PM<sub>2.5</sub> concentrations, at 6.3 µg/m<sup>3</sup>. Another possible explanation with support from the 2019 ISA is that the shape of the concentration-response relationship could differ by health outcome.

Although there were no evaluations of the shape of the long-term PM<sub>2.5</sub>-attributable respiratory mortality relationship in the 2019 PM ISA, there were several studies of the relationship between long-term PM<sub>2.5</sub> exposure and cardiovascular disease. When considering long-term PM<sub>2.5</sub>-attributable cardiovascular mortality, again most results “continue to support a linear, no-threshold relationship...especially at lower ambient concentrations of PM<sub>2.5</sub>...[with] a number of the concentration-response analyses include concentration ranges ≤12 µg/m<sup>3</sup>.” As with total mortality, a few studies found that risk was greater at lower concentrations, although the deviation from linearity was not statistically significant. The only evidence of nonlinearity in the long-term PM<sub>2.5</sub>-attributable cardiovascular mortality relationship came from two studies by the same group, which included exposure from cigarette smoking. They observed that the concentration-response relationship was much steeper at lower PM<sub>2.5</sub> concentrations, such as those due to ambient air pollution, than at the higher concentrations associated with cigarette smoking.

There were a small number of studies of the relationship between long-term PM<sub>2.5</sub> exposure and cardiovascular morbidity endpoints in the 2019 PM ISA. A study of hypertension and another of ischemic heart disease incidence found no deviations from linearity. Two studies of coronary artery calcification found evidence of deviations from linearity, but the direction of the results was inconsistent. One study found evidence of sublinearity at higher concentrations while the other found evidence of supralinearity at both high and low concentrations.

The shape of the relationships between PM<sub>2.5</sub> exposure and health effects may also include a threshold, or PM<sub>2.5</sub> exposure concentration below which human health is not adversely impacted. Although evidence does not currently support the existence of a measurable PM<sub>2.5</sub> exposure population-level threshold, prior higher concentration exposures with longer latency periods could make thresholds difficult to detect. However, the 2019 PM ISA states that “new evidence from recent studies continues to support the previous conclusion that health benefits from reducing air pollution could be expected with a few years of intervention,” reducing the likelihood of this potential source of uncertainty.

Based on the evidence and lack of nonlinear relationships between long-term PM<sub>2.5</sub> exposure and health impacts, we continue to assume a linear, no-threshold relationship and do not quantitatively assess uncertainties related to the shape of the concentration-response relationships



### 6.5.15.2 O<sub>3</sub>

The 2020 final O<sub>3</sub> ISA evaluated a number of studies examining the shape of the concentration-response relationship for long term O<sub>3</sub> exposure and mortality using various different statistical techniques, including linear models and restricted cubic splines, which we use to inform the long-term O<sub>3</sub>-attributable respiratory mortality relationship ((U.S. EPA 2020)). The ISA concluded that:

*Generally linear, no-threshold relationships exist down to 35–40 ppb, although the results were not entirely consistent. Some studies observed a sublinear relationship, indicating larger changes in risk for higher O<sub>3</sub> concentrations compared with lower O<sub>3</sub> concentrations. Several studies also included threshold analyses and support the possibility of a threshold near 35 to 40 ppb. ((U.S. EPA 2020), section 6.2.7)*

The ozone ISA also found that:

*Recent multicity studies continue to support a linear [concentration-response] relationship with no evidence of a threshold between short term ozone exposure and mortality over the range of ozone concentrations typically observed in the U.S. Studies that used different statistical approaches and ozone averaging times (i.e., 24 hour avg and 8 hour max) provide evidence of a linear concentration-response relationship, with less certainty in the shape of the curve at lower concentrations [i.e., 40 ppb for 24 hour avg and 30 ppb for 8 hour max]. An examination of whether a threshold exists in the ozone mortality concentration-response relationship provided no evidence of a concentration below which mortality effects do not occur when examining 5 µg/m<sup>3</sup> (~2.55 ppb) increments across the range of 1 hour max concentrations reported in the U.S. and Canadian cities included in [a large cohort]. ((U.S. EPA 2020), section 6.1.8)*

Collectively, these results continue to support the conclusion of the 2006 Ozone Air Quality Criteria Document that “if a population threshold level exists in ozone health effects, it is likely near the lower limit of ambient ozone concentrations in the U.S.” and this we assume linear, no-threshold relationships exist between ozone and health impacts in the main benefits estimate.

In addition, the studies identified as best characterizing respiratory mortality exposures did not provide threshold models or find evidence supporting a threshold associated with warm-season effects. (Turner, Jerrett et al. 2016) did find “some evidence that a threshold model improved model fit for respiratory mortality at 35 ppb ( $P = 0.002$ ) compared with a linear model using year-round but not summertime O<sub>3</sub> (HR per 10 ppb using threshold O<sub>3</sub> indicator at 35 ppb for respiratory mortality, 1.17; 95% CI, 1.11–1.22).” However, as we are currently unable to obtain all year air quality projections, we are unable to quantitatively assess this year-round-specific uncertainty associated with long-term O<sub>3</sub> exposures.

### 6.5.16 Short-Term Lag Structure<sup>92</sup>

Epidemiologic analyses of short-term exposures often present results as health outcomes occurring a certain time period, or lag days, after exposure. Although there are means of aggregating outcomes that do not occur simultaneously, such as distributed or multi-day lags, there is a possibility that the full impact may not be captured by discrete lag periods in short-term study results. Although uncertainty remains as to whether short-term health impacts are fully captured by discrete lag durations, potentially

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<sup>92</sup> The 2019 PM ISAs includes Table A-1 in its appendix, which describes the lag hierarchy preferences followed when identifying risk estimates for benefits assessment.

biasing results toward the null, we are currently unable perform quantitative uncertainty analyses regarding this source of uncertainty.

#### **6.5.16.1 $PM_{2.5}$**

The 2019 final PM ISA states that “a number of recent studies conducted systematic evaluations of the lag structure of associations for the [short-term]  $PM_{2.5}$  [exposure]-mortality relationship by examining either multiday lags or a series of single-day lags, and these studies continue to support an immediate effect (i.e., lag 0-1 days) of short-term  $PM_{2.5}$  exposures on mortality” ((U.S. EPA 2019)). With respect to morbidity effects, the ISA found that “while recent studies provided evidence of associations in the range of 0-5 days for respiratory effects, there was evidence of an immediate effect for cardiovascular effects and mortality (i.e., 0-1 days) with some initial evidence of associations occurring over longer exposure durations (e.g., 0-4 days).”

#### **6.5.16.2 $O_3$**

The 2020 final  $O_3$  ISA found that “for respiratory health effects, when examining more overt effects, such as respiratory related hospital admissions and ED visits (i.e., asthma, COPD, and all respiratory outcomes), epidemiologic studies reported strongest associations occurring within the 1st few days of exposure (i.e., in the range of 0 to 3 days)” ((U.S. EPA 2020)).

### **6.5.17 Statistical Technique/Model Used to Quantify Risks in Epidemiologic Study**

Multiple statistical techniques are used in epidemiological analyses, including the Cox proportional hazards model and the Poisson survival analysis.

#### **6.5.17.1 $PM_{2.5}$**

The 2019 PM ISA compared the use of various statistical techniques, spatial random effects, and fixed<sup>93</sup> effect models ((U.S. EPA 2019)). The ISA found that “results from well-studied, highly regarded cohorts help to reduce uncertainties that the observed associations between long-term  $PM_{2.5}$  exposure and mortality could be due to the statistical techniques employed or model specification.”

#### **6.5.17.2 $O_3$**

The 2020  $O_3$  ISA found that “studies used a number of different statistical techniques to evaluate the shape of the [long-term exposure] concentration-response function, including linear models and restricted cubic splines, and generally observed linear, no-threshold relationships down to 35–40 ppb, although the results are not entirely consistent” ((U.S. EPA 2020)).

### **6.5.18 Temperature and Weather**

Temperature and weather may impact observed associations between air pollution exposure and health effects in epidemiologic studies, especially in short-term exposure studies. Although a few studies attempt to disentangle the influence of temperature and/or weather, there is insufficient information available to perform quantitative assessments of uncertainty.

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<sup>93</sup> Assumes that there is a single true concentration-response relationship and therefore a single true value for the risk estimate parameter that applies everywhere.

#### 6.5.18.1 $PM_{2.5}$

The PM ISA included a number of studies that assessed whether statistical models adequately account for temporal trends and weather covariates ((U.S. EPA 2019)). The ISA found that:

Across studies that evaluated model specification, [short-term]  $PM_{2.5}$ -mortality, associations remained positive, although in some cases were attenuated, when using different approaches to account for temporal trends or weather covariates. Seasonal analyses continue to provide evidence that associations are larger in magnitude during warmer months, but it remains unclear whether copollutants confound the associations observed. In addition to seasonal analyses, some studies also examined whether temperature modifies the [short-term]  $PM_{2.5}$ -mortality relationship. Initial evidence indicates that the  $PM_{2.5}$ -mortality association may be larger in magnitude at lower and higher temperatures, but this observation has not been substantiated by studies conducted in the U.S. ((U.S. EPA 2019), section 11.1.12)

#### 6.5.18.2 $O_3$

Temperature and weather can also impact epidemiologic results, especially in short-term exposure analyses. While there is limited evidence of differential  $O_3$  mortality associations by season, the 2020  $O_3$  ISA determined that the most extensive analyses conducted by recent studies examined whether temperature (i.e., long-term average temperatures or the distribution of mean daily temperatures) modifies the  $O_3$  mortality association ((U.S. EPA 2020)). Analyses focusing on temperature indicate that locations with lower long-term average temperature have higher  $O_3$  mortality risk estimates, which is also reflected by the observed difference in risk estimates between northern and southern U.S. cities in a single study. However, as long-term average temperature may be a surrogate for air conditioning prevalence and studies that examined either the joint or stratified effects of  $O_3$  and temperature on mortality provided evidence of  $O_3$  mortality associations that are larger in magnitude at temperature extremes, we do not plan on including quantitative uncertainty analyses for the effect of temperature on ozone effects.

#### 6.5.19 Unquantified Impacts

As with all estimates of benefits, due to the lack of complete data, not all human health impacts attributable  $PM_{2.5}$  and  $O_3$  can be identified and quantified. EPA acknowledges the existence of unquantified impacts, such as subclinical health endpoints (e.g., hypertension, inflammation, changes in lung/heart function, etc.) or pollutant-attributable clinical endpoints not evaluated in epidemiologic studies.

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