

Health and economic benefits of reducing air pollution exposure through adaptation and mitigation under a changing climate

by

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Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of Contributions

I (Matt Sparks) was the sole author of Chapters 1, 2, and 6. These chapters were written under the supervision of my supervisor, Dr. Rebecca Saari, and were not written for publication elsewhere.

Chapters 3, 4, and 5 include three manuscripts written for publication. I was the lead author on all of those studies and my contributions to each are detailed below.

Chapter 3 consists of a paper published in the journal *Proceedings of the National Academy of Science of the United States of America* (PNAS). This was an interdisciplinary study, led by myself and my supervisor, in collaboration with experts in climate science, indoor air pollution, public health, and socio-environment systems. I designed the research plan, created the exposure models, conducted the study, analyzed the data, and wrote the manuscript, with assistance from other collaborators and primarily my supervisor. Future pollutant concentrations were provided by Fernando Garcia-Menendez and James East, based on future climate simulations provided by Erwan Monier. Isaiah Farahbakhsh and I developed the Social Learning Model, with significant input from Chris Bauch and Madhur Anand.

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Chapter 4 consists of a manuscript submitted for publication. My collaborators include my supervisor and experts in climate science and air quality modeling. I conceptualized the study design, developed the exposure and adaptation models, conducted the study, analyzed the data, and wrote the manuscript, with assistance from other collaborators and primarily my supervisor. Future pollutant concentrations were provided by Fernando Garcia-Menendez and James East using climate simulations developed by Erwan Monier.

Chapter 5 consists of a manuscript currently under review. My collaborators include my supervisor and other researchers in our field. I conceptualized the study design, created the exposure models, gathered historical data, conducted the study, analyzed the data, and wrote the manuscript, with assistance from other collaborators and primarily my supervisor. Other collaborators include a lab-mate who provided insight based on a related ongoing study, and an expert in indoor air quality.

Abstract

Air pollution is the world's largest environmental health risk. Even in countries with perceived clean air, like the United States of America (U.S.) and Canada, ambient air pollution still contributes to approximately 150,000 and 17,500 annual premature mortalities, respectively.

Air pollution is expected to worsen under climate change, leading to increases in mean ozone and $\text{PM}_{2.5}$ concentrations and higher extreme values. These changes could lead to more air quality alerts, which are triggered when Air Quality Index (AQI) values exceed certain thresholds. Though they are the main medium for communicating air pollution risk to the public, the effect of climate change on air quality alerts has not been previously studied.

The effectiveness of air quality alerts, and the adaptation behaviors they recommend, is also not well known. Few studies have investigated how people respond to air quality alerts, and none have looked at how behavioral responses may change in the future. Even fewer studies quantify the health benefits that adapters, or those who respond to air quality alerts, receive from their adaptation. This is critical to understand, as air pollution is a significant public health threat now and, without emission reductions, is expected to worsen this century.

The studies included in this dissertation use modeled future data to elucidate how air quality alerts driven by $\text{PM}_{2.5}$ and ozone change throughout the 21st century. They identify who is affected by the increase in air quality alerts and model how these populations might respond. The use detailed time use, location, and building parameter data to provide improved estimates of adaptation behaviors.

Across the three studies, we find adaptation - including limiting time outdoors, masking, and reducing infiltration - to be useful in reducing ambient air pollution exposure. However, adaptation benefits are not distributed evenly across the population. Certain populations, like seniors (aged 65+), receive much higher benefits than other groups. So too, do those who have cleaner environments in which to adapt.

Reducing outdoor concentrations, through policy addressing climate change or air pollution, reduces the need to adapt and protects those who cannot adapt. However, the studies herein show that behavioral change must also be considered, as it can either offset or amplify health improvements from ambient pollution reduction.

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Chapter 1

Introduction

1.1 Motivation

The World Health Organization has identified air pollution as the most severe environmental threat to human health [10]. In a global study, Burnett et al. (2018) estimated that 8.9 million excess deaths were attributable to ambient PM_{2.5} pollution in 2015 [11]. Although air pollution levels are lower in North America than in places like India, the Middle East, and China [11], it still leads to a significant health burden. In the U.S., Thakrar et al (2020) found that exposure to ambient air pollution is associated with up to 200,000 premature deaths annually [12]. Health Canada reports that the annual monetized value of air pollution-driven health impacts was \$146 billion (2020 CAD) in 2018 in Canada [13].

To communicate the risk associated with a given level of air pollution, health authorities in the U.S. and Canada use numeric systems. In the U.S., risk is communicated by the Air Quality Index (AQI) [6]. Canada primarily uses the Air Quality Health Index (AQHI) [14]. Both systems link air pollutant concentrations with protective behavioral recommendations. These recommendations prescribe individual actions that are intended to reduce

short-term pollutant exposure. Previous studies have evaluated alternative health index design for high pollution events [15], the communication media through which people receive air quality alerts [16], and compliance with AQI/AQHI recommended actions [5]. While one study has investigated potential health-related economic benefits of air quality warnings [17], we are not aware of any work that studies the size and fairness of the burden they place on individuals who adapt.

The relationship between air pollution, adaptation, and human health impacts will become even more important throughout the 21st century as the effects of climate change progress. Climate change is generally expected to worsen air pollution in the U.S. and Canada, especially in areas with higher populations [18], [19]. This deleterious effect of climate change on air quality is termed the climate penalty. Previous studies show that air pollution health burdens due to the climate penalty could double without climate change mitigation [20], [7].

Policymakers have the opportunity to reduce the impact of future ambient air pollution in three ways: policy to reduce ambient air pollution, climate change mitigation policy, and air pollution adaptation policy. The effects of air pollution policy are well explored elsewhere [21], whereas the effects of the latter two approaches have received less attention. Climate change mitigation policy (or “climate policy”) targets the amount of greenhouse gases (GHG) emitted. Climate policy can reduce air pollution by directly reducing pollutants co-emitted with carbon [22] and by mitigating the climate penalty on air pollution [23]. However, climate policy implementation has been slow so far [24]. While waiting for climate policy to be enacted, and for its effects to emerge, policymakers have an opportunity to protect population health by simultaneously creating adaptation policy that helps

people to protect themselves.

To effectively craft mitigation and adaptation policy, decision-makers must understand how these two systems work together. Health Canada has identified “understanding of how various climate change mitigation and adaptation strategies can affect health and health inequities” as a critical knowledge gap in their recent knowledge assessment report [25]. A recent review, however, studied 10 air pollution adaptation strategies and found “the quality of the evidence is lacking” [26]. Adaptation to and mitigation of climate hazards will continue to be important for human health. This dissertation seeks to develop new methods in order to improve our understanding of both types of policy strategies, and their interactions, in the context of air pollution.

1.2 Research Objective and Questions

The goal of my doctoral research is to investigate the health benefits of reduced air pollution exposure through both adaptation and climate change mitigation. To do so, I, alongside my outstanding colleagues, conducted three individual studies, each focused on the continental United States, which address the research questions listed below.

1. What is the effect on health of individual adaptation behavior in response to ambient $\text{PM}_{2.5}$ in the U.S. using different decision-making strategies under varying levels of climate change mitigation policy?
2. How will ozone and $\text{PM}_{2.5}$ driven air quality alerts change by end-of-century under different climate policy scenarios? What are the health implications for sensitive populations?

3. What was the effect of the COVID-19 pandemic on factors affecting population exposure to $\text{PM}_{2.5}$ of outdoor origin?

My doctoral research advances our understanding of the health impacts of air pollution under both climate change mitigation and individual-level adaptation. It fills a gap noted by Health Canada in evaluating combined effects of mitigation and adaptation on human health and health inequities. It does this specifically for air pollution, which is the leading environmental health risk for premature death globally [10]. Methodologically, it addresses challenges of scale in two ways. First, by studying how large simulations of global climate change impact decisions on an individual level. Second, the proposed research represents the effects that short-term decisions have on long-term health outcomes. By developing decision-making models relevant to adaptation to air pollution, the proposed work also addresses challenges of representing human behavior in MultiSector Dynamics (MSD) or nature-society systems [27, 28]. This research informs policies to sustainably protect human health in a changing climate while providing guidelines for representing adaptation in future research.

1.3 Dissertation Structure

Chapter 2 provides an introduction to literature relevant to the subsequent studies. Chapter 2 was written specifically for this dissertation and was not previously published. Chapter 3 is a reproduction of a study titled “Health and equity implications of individual adaptation to air pollution in a changing climate” that was published in the journal *Pro-*

ceedings of the National Academy of Sciences of the United States (PNAS) in January 2024. Chapter 4 is a reproduction of a manuscript titled “Future Ozone and PM_{2.5} in the US Under Varying Climate Policy: Air Quality Alerts, Health Impacts, and Adaptation Implications” that was submitted for publication. Chapter 5 contains a manuscript titled “Population Exposure to Outdoor Particulate Matter: Role of Buildings, Behavior, Ambient Air Quality, and the COVID-19 Pandemic” currently under review. Chapter 6 is a conclusion chapter that discusses contributions and future work.

Chapter 2

Literature Review

2.1 Introduction

In this section, I introduce background information relevant to the studies included in Chapters 3, 4, and 5. This includes descriptions of air pollutants used in the following studies, their health impacts, and an introduction to the regulatory impact assessment approach for air quality policy. I also introduce the sources of air pollution data used in this work, and the metrics by which air pollution risk is communicated to the public. Lastly, I discuss the existing literature on air pollution adaptation, and identify the research gap that my work fills.

2.2 Relevant Air Pollutants

The atmosphere is composed of 78% N₂, 21% O₂, 0.9% Ar, the last 0.1% being other trace components [29]. The trace gas fraction of the atmosphere contains some compounds which are harmful to human health. These harmful substances are commonly referred to as

contaminants or pollutants. To mitigate the impact that these compounds have on human health, the United States of America (U.S.) government implemented the Clean Air Act [30]. This act requires the U.S. Environmental Protection Agency (EPA) to set standards for six common outdoor air pollutants [31]. These standards are known as the National Ambient Air Quality Standards (NAAQS) [32]. The criteria pollutants within the NAAQS are ground level ozone, particulate matter (PM_x , where x is the maximum aerodynamic diameter of the particle in μm), carbon monoxide (CO), lead (Pb), sulfur dioxide (SO_2), and nitrogen dioxide (NO_2) [33]. Similarly, the Government of Canada has defined its own list of Criteria Air Contaminants (CAC's) [34]. Canada's list includes sulfur oxides (SO_x), nitrogen oxides (NO_x), volatile organic compounds (VOCs), PM_x , CO, ammonia (NH_3), and ground level ozone. There is considerable overlap between the two lists, with five out of the six NAAQS criteria pollutants appearing in Canada's CAC's.

Although the U.S. and Canadian indices include several pollutants, three (ozone, $PM_{2.5}$, and NO_2) most commonly exceed their respective standards [18]. From a public health perspective, most of the burden is due to $PM_{2.5}$, followed by ozone [35]. For most of the population of North America, both $PM_{2.5}$ and ozone concentrations are expected to increase due to climate change, when holding air pollutant emissions constant [20]. For these reasons, this dissertation will focus its analysis on ozone and $PM_{2.5}$. However, for a Canadian context, this literature review will also discuss NO_2 and its role in Canadian air quality alerts. The subsequent sections describes these pollutants, how they are affected by climate change, and their potential impacts on human health.

2.2.1 Ozone

Ozone is a molecule consisting of three oxygen atoms. It is found as a gas throughout the atmosphere. Approximately 90% of atmospheric ozone resides in the stratosphere, between approximately 15 and 35 km above the Earth’s surface [36]. The “ozone layer” resides within that range and benefits human health by limiting the amount of solar radiation that reaches the Earth’s surface. The remaining 10% of atmospheric ozone resides within the troposphere, or within approximately 10 km of the Earth’s surface [37].

Ozone is a secondary air pollutant, meaning that it is not directly emitted, but is instead formed by reactions of primary pollutants in the atmosphere. More specifically, ozone is formed through reactions between NO_x and VOCs in the presence of heat and sunlight [38]. Because they require heat and sunlight, these formation processes are weather sensitive, meaning that they will be affected by climate change. Climate change affects several atmospheric processes that will impact tropospheric ozone levels that human populations are exposed to [19]. Fu and Tian (2019) reviews several previous studies and finds that climate change will increase ozone concentrations over the U.S., with significant spatial variation and year-to-year variability [19].

2.2.2 $\text{PM}_{2.5}$

$\text{PM}_{2.5}$ is not a single compound, but a class of airborne substances with an aerodynamic diameter of $2.5 \mu\text{m}$ or less. $\text{PM}_{2.5}$ is both a primary pollutant and a secondary pollutant, which means that it is emitted directly into the atmosphere and also forms there through reactions of precursors. The primary sources of $\text{PM}_{2.5}$ are sea salt, mineral dust, and

combustion by-products such as black and organic carbon [18]. The secondary components of $\text{PM}_{2.5}$ include sulfate, ammonium nitrate, and other secondary organic aerosols [18]. $\text{PM}_{2.5}$ typically remains airborne on a time scale of days to weeks until it is deposited, either by rain or settling [29]. In Canada, the largest source of $\text{PM}_{2.5}$ is wildfires, followed closely by transportation, residential combustion, and industry [39].

Because the formation and transport of $\text{PM}_{2.5}$ are influenced by weather, climate change will have a strong impact on future population's $\text{PM}_{2.5}$ exposure. It is, however, unclear exactly how climate change will impact atmospheric $\text{PM}_{2.5}$ concentrations. In a warmer, more drought-prone world, dust is more likely to become airborne and fewer rain events may occur to remove the airborne particulate matter [18]. At the same time, aerosol abundance in the atmosphere enables cloud formation, potentially leading to increased cooling and precipitation, but the mechanisms and modeling of this phenomenon are still uncertain [40]. Overall, it is expected that climate change will lead to increases in $\text{PM}_{2.5}$ concentrations across the U.S. [20] and Canada [41].

2.2.3 NO_2

NO_x , or nitrogen oxides, are a group of gaseous air pollutants that include NO and NO_2 . These pollutants are typically formed in the combustion process, coming from the nitrogen contained in both the fuel and the air used in the reaction [42]. Both NO and NO_2 are primary, or directly-emitted, pollutants and are commonly associated with the transportation, electricity generation, and heavy equipment sectors [42].

NO oxidizes quickly after it is emitted, which turns it into NO_2 . Therefore, NO_2 is the

pollutant that gets measured and reported [43]. NO_2 also contributes to the formation of both $\text{PM}_{2.5}$ and ozone. NO_2 oxidizes to form nitrate aerosols, a form of $\text{PM}_{2.5}$ [18]. As mentioned in Section 2.2.1, NO_2 is also a key component of ground-level ozone formation. The impact of climate change on NO_2 concentrations is complicated. On one hand, higher NO_2 levels lead to lower methane levels and lower global warming potential [18]. However, climate policy that reduces combustion (e.g., incentivising switching to electric cars) is likely to decrease NO_2 concentrations and exposure [44].

2.3 Health Impacts

2.3.1 Ozone

Ozone is a potent air pollutant that is associated with several adverse health outcomes. Increases in short-term ambient ozone exposure are associated with increases in respiratory-driven mortality [45, 46], hospital admissions [46], emergency department visits [47], and asthma symptoms in children [48]. Increases in long-term ozone exposure are associated with mortality [49], asthma onset in children [50], and allergic rhinitis in children [51]. The mechanisms by which ozone pollutant exposure leads to mortality and morbidity are complex. In general, ozone exposure leads to respiratory inflammation, oxidative stress, and potential injury. This can lead to altered lung morphology and increase the severity of diseases like influenza, which can lead to premature death [52].

2.3.2 PM_{2.5}

Increases in PM_{2.5} concentration are harmful to human health. Outdoor PM_{2.5} concentration has been found to be a predictor of premature mortality [53, 11, 54, 55] and many other morbidities such as acute myocardial infarction [56], cardiac arrest [57], stroke [58], asthma [50], and lung cancer [59]. Globally, PM_{2.5} is responsible for over 90% of air pollution related premature deaths [35]. PM_{2.5} molecule inhalation leads to systemic inflammation and oxidative stress as PM_{2.5} is small enough to be transported within bodily tissue. This leads to impaired vascular function, atherosclerosis, hypertension, and thrombosis - causing the adverse outcomes listed above [60].

PM_{2.5} disproportionately affects vulnerable people in the U.S. Racial-ethnic minorities have local outdoor concentrations higher than other demographic groups [61] but there was a decreasing trend in racial-ethnic concentration disparity between 1990 - 2010 [62]. PM_{2.5} is particularly harmful to those with underlying health conditions, racial-ethnic minorities, and the elderly [63].

2.3.3 NO₂

NO₂ is a harmful substance for both humans and the environment. Environmentally, NO_x species react with water, oxygen, and other atmospheric chemicals to produce acid rain [43]. Similarly, NO₂ is highly reactive within the human body [52]. Inhalation of NO₂ has been deemed to cause short-term respiratory effects such as asthma attacks [52]. Increases in short-term local concentrations have also been found to be associated with increased mortality risk in Canada [64]. Long-term exposure has been found to cause

persistent airway inflammation and oxidative stress, which leads to increased risk of asthma development [52]. Increases in local NO₂ concentrations have also been associated with an increased mortality risk [65].

2.3.4 Regulatory Analysis

Decreasing outdoor pollutant concentrations can prevent the health impacts mentioned in Sections 2.3.1, 2.3.2, and 2.3.3. Doing so typically requires implementing regulations that require polluters to reduce pollutant emissions [66]. The EPA provides guidelines for comparing the benefits, e.g., avoided adverse health and environmental effects, against the costs, e.g., more expensive pollution control equipment [67].

The first step to calculating the benefits of a regulatory policy is to quantify the impact that the policy will have. For air pollution, this typically means using a chemical transport model (CTM) to translate changes in emissions to changes in ambient air quality [68]. From there, changes in endpoints are determined. These endpoints can include environmental damages, material damages, and aesthetic improvements, but the work in this dissertation will focus on changes in human health outcomes. Health outcome changes are assessed through a Health Impact Function (HIF) that relates changes in outdoor pollutant concentrations with population characteristics. The EPA provides an open-source software solution for this called the Environmental Benefits Mapping and Analysis Program - Community Edition (BenMAP - CE) [69].

The changes in health outcome incidence (e.g., changes in premature mortality, asthma, or cancer) are then typically translated to dollar values. Some of these outcomes have

market value, such as the cost of cancer treatment, but many do not. These items are captured through willingness to pay (WTP). WTP is the EPA’s preferred measure for benefits [67] and represents one’s willingness to trade money for a reduced risk of an adverse health outcome. When aggregated over populations, the WTP to avoid the risk equal to one premature death is commonly called the Value of a Statistical Life (VSL) [70]. To reiterate, the VSL reflects the WTP for individuals to have a small change in mortality risk, normalized to one expected avoided death across an entire population. It does not measure the value of a human life or how much one person would pay to avoid certain death [67, 71].

Regulatory costs can be estimated in a few ways. First, direct compliance costs, e.g., to purchase pollution control equipment, can be calculated for individual sites, and summed across industries. Costs included in regulatory evaluation can also include costs associated with government administration, oversight, and monitoring [67]. Other indirect economic costs are more difficult to measure. However, Chapters 3 and 4 use previously published results of a Computable General Equilibrium (CGE) model [72]. CGEs balance supply and demand across multiple sectors and countries over time to determine the effect of a regulatory policy. They can account for indirect effects of policy, including shifts in prices and demand across markets. As such, they are suitable for evaluating policies with the potential for significant price implications across markets, such as a carbon tax, which is the climate change mitigation policy we evaluate in this work.

Because both the market and non-market benefits of environmental policy are monetary values, they are often compared with monetary costs. Significant regulations in the U.S. and Canada are required to calculate the net-benefits, or benefits minus costs [67]. Net

benefits of adaptation are evaluated in this dissertation.

2.4 Air Pollution Data Sources

The studies included in this dissertation make use of both measured and modeled air pollution data. This section provides a brief explanation for how data from both sources is gathered for this work.

2.4.1 Measured Data

In the U.S., the EPA provides air quality data through their AirNow portal [73]. AirNow provides a central resource for air pollution forecasts and monitor data in the U.S. The work included in this dissertation uses the AirData portion of the website, which provides both pre-generated data files and raw data through an Application Programming Interface (API) [74]. Daily pollution datasets are provided for ozone and PM_{2.5} from 1980 - 2024. Data is available aggregated at the monitor, county, and core-based statistical area (CBSA) level. The studies in this dissertation use only the highest quality data collected via EPA Federal Reference Methods and Federal Equivalent Methods [75].

2.4.2 Integrated Modeling Frameworks

A powerful tool for conducting interdisciplinary climate change research is an Integrated Assessment Model (IAM) [76]. IAMs are defined as having four parts [77]. First, they capture both the economic and natural process that produce greenhouse gas (GHG) emissions. Next, modeled GHG emissions drive the carbon cycle and, thirdly, change the chemical

composition of the atmosphere. Lastly, carbon cycle changes result in long-term climate variable changes, which impact Earth’s natural systems [77]. These early IAMs were able to estimate aggregate economic damages. They originally used simplified damage functions, and were criticized for it [78], but they remain a preeminent tool used to provide policy-relevant insights for the United Nations Framework Convention on Climate Change [60].

A similar but distinct approach, used in this research, are Integrated Modeling Frameworks [79]. Instead of applying one or more damage functions, IMFs couple human-Earth systems. Changes in the Earth system are then used as input to various impact models, e.g., associated with water stress, agriculture, or health. IMFs have been applied for decades to represent the policy-to-impacts pathway for air pollution [80].

IMFs are uniquely suited to studying air pollution concentrations and their corresponding health benefits under different climate futures. An early global meta-analysis by Nemet et al. (2010) found the range of reduction in air pollution health burden to be between \$2 - \$196 USD (2008) per emitted ton of CO_2 avoided [81]. Monetized alleviation of the health burden was found to be largest in developing countries [81]. Around the same time, Tagaris et al. (2009)¹, showed that climate change would lead to adverse health outcomes for 2/3 of the continental U.S, particularly in the northern portions of the country [82]. They showed that this increased health burden would be driven primary by changes in $PM_{2.5}$ concentrations, although there was high uncertainty in how $PM_{2.5}$ concentrations would change [82]. Global studies by Selin et al. (2009)² and West et al. (2013) further

¹This study was published before Nemet et al. (2010), but not within the time frame to be included in that review.

²Similarly to Tagaris et al (2009), this paper was published outside of the scope of the Nemet et al.

clarify that the health-related economic benefits of reducing air pollution through mitigating climate change are high in North America [83, 9]. These are called the air pollution related co-benefits of climate policy.

After establishing a generally positive global correlation between climate policy and reductions in air pollution, recent studies focused on higher resolution representation of the U.S. Initial studies focused on benefits that of reducing pollutants that were “co-emitted” alongside carbon. Thompson et al., (2014) looked at the spatial differences between $\text{PM}_{2.5}$ and ozone concentrations across the U.S. under carbon-mitigation policy targeted for the electricity and transportation sectors as well as an economy-wide cap and trade policy - finding that the median annual air quality health benefits of the cap and trade policy outweighed policy costs several times over, with most of the benefit occurring in the eastern U.S. [84]. Saari et al. (2015) found that $\text{PM}_{2.5}$ related benefits can offset the costs of cap and trade carbon policy that reduces U.S. emissions 10% from 2006 - 2030 [85]. The first study to isolate the climate penalty effect on air pollution, Garcia-Menendez et al. (2015), investigated future U.S. air pollution under a reference scenario and two climate change mitigation scenarios driven by a global carbon tax. They found that national population-weighted $\text{PM}_{2.5}$ exposure was lowest under the most stringent climate policy, driving mean health benefits that offset 5% of policy cost in 2050 and 15% of policy cost in 2100 [20]. In Canada, the effect of climate change on air pollution was not studied until very recently, when Shim (2021) found that $\text{PM}_{2.5}$ increases under climate change, but that climate policy can mitigate that increase, leading to tens of billions of dollars of health benefits annually by end of century [41].

(2010) review.

2.5 Air Pollution Metrics

Both the U.S. and Canada have monitoring programs that regularly measure air pollution concentrations and communicate their corresponding health risks to the public. The U.S. quantifies and communicates air pollution health risk with Air Quality Index (AQI) [6]. Canada uses the Air Quality Health Index (AQHI) [14].

2.5.1 Air Quality Index

As mentioned in Section 2.2, the EPA sets National Ambient Air Quality Standards (NAAQS) for the outdoor concentrations for six pollutants [32]. These include primary standards, which are meant to protect public health, and secondary standards, which are meant to improve public welfare and decrease the risk of damage to crops, buildings, and animals [32]. The NAAQS focus on short-term health impacts of air pollution, typically involving health impacts occurring within hours or days of exposure [86].

The Air Quality Index (AQI) measures how close outdoor concentrations are to meeting NAAQS [32]. Typically, an AQI value of 100 corresponds to the NAAQS standard for that pollutant. For example, the primary and secondary 24-hour standard for $\text{PM}_{2.5}$ is $35.4 \mu\text{g}/\text{m}^3$ [32]. This concentration is allowed to be the 98th percentile daily concentration over a 3-year period. Similarly, the primary and secondary standard for ozone is an 8-hour concentration of 70 parts per billion (ppb). This concentration is allowed to be the annual fourth-highest daily maximum 8-hour concentration (the highest consecutive 8-hour average in a day) averaged over a 3-year period. As shown in Table 2.1, $\text{PM}_{2.5}$ concentration of $35 \mu\text{g}/\text{m}^3$ and ozone concentration of 70 ppb correspond to AQI values of

100.

AQI values are calculated by linearly interpolating between thresholds defined within the NAAQS for each pollutant. AQI values are calculated individually for each pollutant. The highest AQI value is reported as that location’s AQI, and the corresponding pollutant is the “responsible pollutant”. The ranges for the pollutants relevant to the studies described herein are shown in Table 2.1

Table 2.1: AQI calculation for PM_{2.5}, ozone, and NO₂.

AQI Range	Category	PM _{2.5} Range $\mu\text{g}/\text{m}^3$ 24-hour	Ozone Range ppb 8-hour	NO ₂ Range ppb 1-hour
0-50	Good	0 - 12	0 - 54	0 - 53
51 - 100	Moderate	12.1 - 35.4	55 - 70	54 - 100
101 - 150	Unhealthy for Sensitive Groups	35.5 - 55.4	71 - 85	101 - 360
151 - 200	Unhealthy	55.5 - 150.4	86 - 105	361 - 649
201 - 300	Very Unhealthy	150.5 - 250.4	106 - 200	650 - 1249
301 - 500	Hazardous	250.5 - 500.4	405 - 604 1-hour	1250 - 2049

It bears repeating that, while concentrations may be measured for all six NAAQS air pollutants, reported AQI values are only based on the highest one. Calculating AQI with this method does not account for any additive or complementary effects that different pollutants have on people’s health. Researchers have questioned this procedure [87], and subsequent studies have found that AQI can adequately communicate risk during simple outdoor pollution episodes [88], but might not be associated with all health outcomes [89].

AQI values are required to be communicated to the public for municipalities of over 350,000 people [90]. However, the method of communication is not specified. Current and forecasted AQI data are available through the U.S. government’s AirNow website (airnow.gov). Municipalities can also report their AQI through local news outlets or telephone hotlines [91].

2.5.2 Air Quality Health Index

Canada currently uses the Air Quality Health Index (AQHI) to communicate the health risks of air pollution to the public. There were two main goals when developing the AQHI. The first was to tie pollutant concentrations to measured health risks rather than national standards [14]. Second, the AQHI wanted to incorporate the adverse health effects of multiple pollutants, rather than a single-pollutant metric like AQI [14]. AQHI was determined based on aligning time series data for pollutant concentrations and mortality data across 12 Canadian cities. The metric is calculated as the sum of excess short-term mortality risk for three pollutants (ozone, $PM_{2.5}$, and NO_2) [14] and has been found to be associated with health outcomes [15].

In the AQHI framework, the previous 3-hour average concentrations of ozone, $PM_{2.5}$, and NO_2 are measured. Then, the combined short-term mortality risk is calculated based on the three pollutant concentrations on a scale from 1-10+ and reported. AQHI is calculated using Equation 2.1.

$$AQHI = \frac{10}{10.4} \times 100 \times (e^{(0.000871 \times NO_{2,3-hr})} - 1 + e^{(0.000537 \times O_{3,3-hr})} - 1 + e^{(0.000487 \times PM_{2.5,3-hr})}) \quad (2.1)$$

2.6 Adapting to Air Pollution

Air quality metrics provide information about the danger associated with air pollution concentrations. Alongside that information, they also provide guidance about how to reduce one’s risk. In this dissertation, action taken to reduce one’s exposure to air pollution is defined as adaptation.

The U.S. EPA recommendations for protecting health against ozone and $\text{PM}_{2.5}$ pollution at various levels are shown in Figures 2.1 and 2.2 from the AirNow website [73]. The recommendations are similar for both pollutants. In both cases, the “Good” AQI category comes with no warning about health impacts. In the “Moderate” AQI range, “unusually sensitive people” are told to consider reducing the duration and intensity of outdoor activities. Sensitive people are usually considered to include the elderly, children, infants, pregnant women, and people with underlying health conditions. The “Unhealthy for Sensitive Groups” threshold is where the AQI becomes more strongly worded. Sensitive groups are recommended to make outdoor activities shorter and less intense. Those with asthma are warned to keep relief medicine nearby and the general population is asked to consider shortening and easing outdoor activities. The remaining categories become sequentially more strongly worded to reduce and avoid outdoor time as the AQI gets higher, with sensitive groups being one step more cautious than the general population.

When AQI levels reach certain thresholds, such as “Unhealthy for Sensitive Groups” (100) or “Unhealthy” (150), alerts can be issued to the public to make them aware of the health risk and provide adaptation information. Air quality alerts have been found to reduce outdoor activities like cycling [92] and zoo attendance [93]. These alerts appear to

Air Quality Index	Who Needs to be Concerned?	What Should I Do?
Good (0-50)	It's a great day to be active outside.	
Moderate (51-100)	Some people who may be unusually sensitive to ozone.	Unusually sensitive people: Consider making outdoor activities shorter and less intense. Watch for symptoms such as coughing or shortness of breath. These are signs to take it easier. Everyone else: It's a good day to be active outside.
Unhealthy for Sensitive Groups (101-150)	Sensitive groups include people with lung disease such as asthma, older adults, children and teenagers, and people who are active outdoors.	Sensitive groups: Make outdoor activities shorter and less intense. Take more breaks. Watch for symptoms such as coughing or shortness of breath. Plan outdoor activities in the morning when ozone is lower. People with asthma: Follow your asthma action plan and keep quick-relief medicine handy. Everyone else: Consider making outdoor activities shorter and less intense.
Unhealthy (151-200)	Everyone	Sensitive groups: Do not do long or intense outdoor activities. Schedule outdoor activities in the morning when ozone is lower. Consider moving activities indoors. People with asthma: Follow your asthma action plan and keep quick-relief medicine handy. Everyone else: Reduce long or intense outdoor activity. Take more breaks, do less intense activities. Schedule outdoor activities in the morning when ozone is lower.
Very Unhealthy (201-300)	Everyone	Sensitive groups: Avoid all physical activity outdoors. Move activities indoors* or reschedule to when air quality will be better. People with asthma: Follow your asthma action plan and keep quick-relief medicine handy. Everyone else: Avoid long or intense outdoor exertion. Schedule outdoor activities in the morning when ozone is lower. Consider moving activities indoors.*
Hazardous (301-500)	Everyone	Everyone: Avoid all physical activity outdoors.* People with asthma: Follow your asthma action plan and keep quick-relief medicine handy.

***Note:** If you don't have an air conditioner, staying inside with the windows closed may be dangerous in extremely hot weather. If you are hot, go someplace with air conditioning or check with your local government to find out if cooling centers are available in your community.

Figure 2.1: Guide from AirNow [1] with recommendations of adaptation for sensitive and non-sensitive groups for different ozone-driven AQI values.

mildly reduce health impacts from pollution. A study in Toronto found that air quality alert announcements reduced asthma-related emergency department visits [94]. Alari et al. (2021) found that air quality alerts in Paris, France lead to reductions in cardiovascular

Air Quality Index	Who Needs to be Concerned?	What Should I Do?
Good (0-50)	It's a great day to be active outside.	
Moderate (51-100)	Some people who may be unusually sensitive to particle pollution.	Unusually sensitive people: Consider making outdoor activities shorter and less intense. Watch for symptoms such as coughing or shortness of breath. These are signs to take it easier. Everyone else: It's a good day to be active outside.
Unhealthy for Sensitive Groups (101-150)	Sensitive groups include people with heart or lung disease, older adults, children and teenagers, pregnant women, minority populations, and outdoor workers.	Sensitive groups: Make outdoor activities shorter and less intense. It's OK to be active outdoors, but take more breaks. Watch for symptoms such as coughing or shortness of breath. People with asthma: Follow your asthma action plan and keep quick relief medicine handy. People with heart disease: Symptoms such as palpitations, shortness of breath, or unusual fatigue may indicate a serious problem. If you have any of these, contact your health care provider.
Unhealthy (151-200)	Everyone	Sensitive groups: Avoid long or intense outdoor activities. Consider rescheduling or moving activities indoors.* Everyone else: Reduce long or intense activities. Take more breaks during outdoor activities.
Very Unhealthy (201-300)	Everyone	Sensitive groups: Avoid all physical activity outdoors. Reschedule to a time when air quality is better or move activities indoors.* Everyone else: Avoid long or intense activities. Consider rescheduling or moving activities indoors.*
Hazardous (301-500)	Everyone	Everyone: Avoid all physical activity outdoors. Sensitive groups: Remain indoors and keep activity levels low. Follow tips for keeping particle levels low indoors.*

***Note:** If you don't have an air conditioner, staying inside with the windows closed may be dangerous in extremely hot weather. If you are hot, go someplace with air conditioning or check with your local government to find out if cooling centers are available in your community.

Figure 2.2: Guide from AirNow [2] with recommendations of adaptation for sensitive and non-sensitive groups for different PM_{2.5}-driven AQI values.

mortality, as long as the thresholds are significantly low enough to encourage adaptation [95].

The subsequent sections describe two of the most common types of air pollution adaptation strategies, changing one’s behavior and cleaning one’s indoor environment.

2.6.1 Behavioral Change

As recommended by the AQI charts in Figures 2.1 and 2.2, the primary adaptation strategy for avoiding ambient air pollution in the U.S. is moving indoors [5]. Public responses to alerts vary with awareness, risk perception, social influences, and other factors [5, 96]. Currently, 15 to 20% of Americans adapt to poor air quality, primarily by restricting their time outdoors [5, 97]. The American Thoracic Society is careful to state that populations should not completely reduce physical activity when adapting, but should rather shift it to locations and times when pollution levels are lower [98].

There has previously been little research on the effectiveness of air pollution adaptation. A review found that the strength of evidence supporting six adaptation strategies was a “C” at best [26]. A study on AQI recommendations impact on heart disease had to make “plausible estimates” on the effectiveness of strategies because quantitative measurements did not exist [99]. The most thorough study on air quality adaptation benefits was Buonocore et al. (2021). In that study, they focused on reducing mortality risk for elderly populations in Denver, Los Angeles, and Pittsburgh. The adaptation they simulate is a population staying indoors for the highest AQI hour between 6 am and 9 pm on an alert day. They found a range of \$3.20 to \$14.00 per hour of adaptation depending on the HIF used [17].

2.6.2 Building Improvements

People in the U.S. spend almost all (over 90% on average) of their time indoors [100]. This means that most (roughly 65% per Fisk (2015)) of people’s exposure to ambient, outdoor-generated air pollution actually occurs indoors [101]. Buildings offer different levels of protection from outdoor air depending on their air-tightness, filter efficiency, and ventilation system characteristics [102]. This protective factor is called the infiltration factor (F_{INF}) and is a measure of the fraction of an air pollutant that enters indoors and remains airborne [103]. F_{INF} values for $\text{PM}_{2.5}$ ranges from 1-2% in newly constructed homes [104] with closed windows to near 100% in scenarios where people have windows and doors wide open.

Exposure differences across different indoor environments lead to much different exposure outcomes over time between people. On average, households with lower income are more likely to live in older houses [105], which are generally leakier, leading to higher ambient air pollution exposure. The U.S. Weatherization Assistance Program (WAP) is an initiative that attempts to alleviate this discrepancy by reducing the leakiness of houses for low-income households. A previous study found that energy retrofits in the U.S. reduced leakage by 26% on average [106]. This weatherization process also reduces energy consumption, which, in most places, reduces CO_2 emissions and reduces air pollutants that air emitted during energy generation [107].

A few studies have investigated reducing F_{INF} for $\text{PM}_{2.5}$ into buildings by improving mechanical ventilation filtration effectiveness [104, 108]. These studies have found that the benefits of increasing $\text{PM}_{2.5}$ filtration outweigh the costs in many scenarios, especially

those with high outdoor pollutant levels and for people who are more susceptible to the health impacts of air pollution [104, 108].

2.7 Identified Research Gaps

I identified several gaps in the research that I sought to address. First, while several of the studies in Section 2.4.2 find changes in future pollutant concentrations under climate change, none of them translate these changes into AQI - the primary air pollution communication medium in the U.S. There were no previous studies about how numbers of air quality alerts would change in the future and which pollutants they would be driven by. Also, no previous studies had identified which populations experience changes in air quality alerts due to climate change.

I then decided to study how people might respond to changes in air quality alerts. There are observational studies about changes in movement or outdoor time under current pollution levels, but nothing projecting behavior change into the future. There was also a lack of insight into adaptation effectiveness, or how much adapting could reduce exposure to air pollution. As few studies had done so, we also saw an opportunity to extend our adaptation framework to model the health benefits of adaptation and contrast them with potential costs.

An important gap in the literature that we noticed was the general lack of consideration for exposure across different microenvironments. Most exposure studies look only at changes in outdoor concentration, even though people spend most of their day indoors, and their exposure to outdoor air pollution is modulated by their buildings. We saw an

opportunity to bridge the indoor and outdoor environments and use time use survey data to get a holistic view of outdoor air pollution exposure. This approach allowed us to investigate how exposure changed during the COVID-19 pandemic, a time of massive behavior change. This approach also allowed us to improve understanding of alternative adaptation approaches and to inform more fair and effective adaptation policy.

Chapter 3

Health and Equity Implications of Individual Adaptation to Air Pollution in a Changing Climate

The work in this chapter has been previously published in the *Proceedings of the National Academy of Sciences of the United States of America*. In this version, additional methods information previously included in the Supporting Information document has been moved to the main text for clarity.

3.1 Abstract

Future climate change can cause more days with poor air quality. This could trigger more alerts telling people to stay inside to protect themselves, with potential consequences for health and health equity. Here, we study the change in U.S. air quality alerts over this century due to fine particulate matter (PM_{2.5}), who they may affect, and how they may respond. We find air quality alerts increase by over one month per year in the eastern

U.S. by 2100, and quadruple on average. They predominantly affect areas with high Black populations and leakier homes, exacerbating existing inequalities and impacting those less able to adapt. Reducing emissions can offer significant annual health benefits (\$5,400 per person) by mitigating the effect of climate change on air pollution and its associated risks of early death. Relying on people to adapt, instead, would require them to stay inside, with doors and windows closed, for an extra 142 days per year, at an average cost of \$11,000 per person. It appears likelier, however, that people will achieve minimal protection without policy to increase adaptation rates. Boosting adaptation can offer net benefits, even alongside deep emission cuts. New adaptation policies could, for example: reduce adaptation costs; reduce infiltration and improve indoor air quality; increase awareness of alerts and adaptation; and provide measures for those working or living outdoors. Reducing emissions, conversely, lowers everyone's need to adapt, and protects those who cannot adapt. Equitably protecting human health from air pollution under climate change requires both mitigation and adaptation.

3.2 Significance Statement

Air pollution is the leading environmental risk factor for early death. Alerts guide people to stay indoors when air quality is poor. Climate change can worsen air quality over this century. We show this creates conditions for rising air quality alerts, disproportionately for racialized, unhoused, and poorly housed populations. Relying on people to protect themselves likely offers minimal benefits compared to reducing emissions; however, boosting adaptation can offer additional health benefits even under stringent climate policy. New

policy could, for example, compensate people for moving indoors, and improve access to clean indoor air. We address active policy questions about how to equitably protect health under climate change, identifying levers for action against an increasing, unfair burden of air pollution.

3.3 Introduction

Air pollution is the largest environmental threat leading to premature death [11] worldwide [35]. It disproportionately affects vulnerable people in the United States (U.S.), including in racialized [61] and socio-economically disadvantaged [109] populations. On days with poor air quality, health authorities issue alerts guiding people to protect themselves by limiting their exposure to outdoor air. Alerts are triggered using an aggregate measure of air quality called the Air Quality Index (AQI) [6]. Public responses to alerts vary with awareness, risk perception, social influences, and other factors [5, 96]. Currently, 15-20% of Americans adapt to poor air quality, primarily by restricting their time outdoors [5].

Thanks to decades of improving air quality, alerts are rare for most Americans. Those improvements are at risk, however, due to climate change [20]. While the literature on air quality alerts has examined their construction [15], communication [110, 111, 112], and compliance [5, 96], there is only one recent study of their health or economic value (focusing on the population over age 65 during 2014-2017) [17], and none on the effect of climate change and climate policy.

Climate change can worsen air quality [20, 18, 113]. Climate policy can offer significant [9, 84, 85, 22, 114, 115, 116] and equity-improving [117] health benefits by improving

air quality. Increasing adaptation could also reduce health risks. This has been shown empirically for the case of adapting to extreme temperature [118], but not yet examined for air pollution.

Here, we ask, “How many more air quality alerts may be triggered by climate change? Who will experience this rise in alerts, and how might it affect their health risks, and behavior to reduce those risks? How does that adaptation behavior affect health risks, and the associated benefits of climate policy? What can policymakers do to equitably address rising risks?”

To evaluate these questions, we estimate the rise in air quality alerts the in U.S. over this century due to climate change. We focus on the most harmful pollutant – outdoor fine particulate matter ($\text{PM}_{2.5}$) – and its effects on the AQI and on premature death among adults [119].

We examine which populations are affected, their capacity to adapt to rising risks of premature death by moving indoors, and their per capita costs and benefits of adapting. We assess the extent to which people can compensate for their rising health risks by adapting. We examine the effectiveness of current practice, and identify policy levers to promote adaptation. We compare the health benefits of adaptation – moving indoors to reduce exposures to outdoor air – to those of mitigation – reducing emissions to slow climate change and improve air quality.

To do this, we introduce estimates of the costs and benefits of adapting to outdoor air pollution by moving indoors. We quantify costs as foregone outdoor time, valued at the wage rate. We base benefits on the reduction in annual mean exposure to outdoor air pol-

lution ($\text{PM}_{2.5}$), achieved via daily decisions to stay indoors. Outdoor $\text{PM}_{2.5}$ concentrations are from our prior work, covering the contiguous U.S. on a $1.9^\circ \times 2.5^\circ$ grid [7]. We account for exposure to outdoor $\text{PM}_{2.5}$ while indoors via the infiltration factor (i.e., the fraction of outdoor $\text{PM}_{2.5}$ that enters indoors and remains airborne) [103]. The resulting reduction in exposure to outdoor $\text{PM}_{2.5}$ lowers the risk of premature death from all causes, estimated with a concentration-response function relating outdoor $\text{PM}_{2.5}$ to health risks [55] and valued based on willingness-to-pay to reduce that risk, following U.S. regulatory impact analysis [120]. We explore the potential for adaptation to protect health by considering a range of ways in which the population in each grid cell may decide to adapt, including: complying with alerts issued at current or lowered $\text{PM}_{2.5}$ concentration thresholds (“Threshold”), complying with alerts based on the behavior of others (“Social Learning”), adapting on days for which their benefits exceed their costs (“Rational Actor”), and adapting to offset their rising health risks by as much as climate change mitigation (“Forced”). We perform distributional and sensitivity analyses to identify variables that influence the net benefits of adapting, and to assess the uncertainty, variability, and equity implications of adaptation and adaptation policy.

We find that air quality alerts could increase steeply by the end of this century, especially in areas with high Black populations, higher incomes, and leakier homes. Moving indoors (adaptation) could theoretically be as protective of health as reducing emissions of outdoor air pollutants (mitigation), but that would likely come at a net cost and significant loss of outdoor time. Conversely, mitigation protects those who do not or cannot adapt. Even with mitigation, however, policy to promote more adaptation can offer net benefits. Such policy could, for example, lower adaptation costs or improve indoor air quality.

3.4 Methods

3.4.1 Air Quality Concentrations

This work derives future air quality concentrations from previous work [20, 7, 121]. That work employed the Massachusetts Institute of Technology (MIT) Integrated Global System Model (IGSM) framework [8]. This framework links a global computable general equilibrium economic model (Economic Projection and Policy Analysis (EPPA)), an earth system model of intermediate complexity (MIT Earth System Model (MESM)), and an air quality model (the National Center for Atmospheric Research (NCAR) Community Atmosphere Model with Chemistry (CAM-Chem)) to generate air pollution concentrations for scenarios as in [20, 7, 121] and summarized in Table A.6. Modeled pollutant concentrations correspond well with measured values, with year 2000 national simulated annual population weighted PM_{2.5} concentration within 7% of the EPA’s reported national average [121].

3.4.2 Air Quality Alerts

Air quality alerts are typically issued when the Air Quality Index (AQI), as defined by the U.S EPA [6], exceeds a threshold. We study the current thresholds for the general (150) and sensitive (100) populations. In practice, AQI values are calculated separately for multiple pollutants, and the highest value is reported as the AQI. For this study, we only consider PM_{2.5} concentrations, with AQI thresholds of 100 and 150 corresponding to 24-hour mean PM_{2.5} concentrations of 35.4 $\mu\text{g}/\text{m}^3$ and 55.4 $\mu\text{g}/\text{m}^3$, respectively.

3.4.3 Adaptation Net Benefits

We model adaptation behavior in the adult (age 25-99) contiguous U.S. population. We represent avoidance – moving indoors to reduce exposure – the current dominant mode of adaptation [5]. Daily 24-mean $PM_{2.5}$ concentrations are analyzed at the air quality model grid scale ($1.9^\circ \times 2.5^\circ$) for each annual simulation. Annual simulations represent three sets of three decades, including 1981-2010, 2036-2065, and 2086-2115, for each of five sets of initial climate conditions. We average results to estimate conditions at start, mid, and end-of-century under a reference (REF) and climate policy scenario (P3.7). Population and demographic data are aggregated to the air quality model grid. Populations make daily adaptation decisions. The value of adapting on a given day d is described its net benefits per Equation 3.1.

$$NB_d = B_d - C_d \quad (3.1)$$

Where NB_d is the net benefits of adapting on day d , calculated as B_d , the benefits of adapting on day d , minus C_d , the cost of adapting on day d .

3.4.4 Adaptation Benefits

Adaptation lowers daily $PM_{2.5}$ exposure, which also lowers annual average exposure, reducing the incidence rate of premature mortality. The equivalent daily benefit of this risk reduction is shown in equation 3.2.

$$B_d = VSL \times \Delta I_d \quad (3.2)$$

Where VSL represents the Value of a Statistical Life, and ΔI_d is the change in incidence rate of premature mortality achieved by adapting on day d.

VSL is a measure of willingness-to-pay to reduce the risk of premature mortality. We use the most recent value provided by the U.S. EPA, based on a review of 26 studies, 7.9 million USD (2008) [122]. We calculate the change in incidence of premature mortality from all causes from adapting on day d with equation 3.3.

$$\Delta I_d = Y_0 \times ((RR - 1)/RR) \times (\Delta PM_{2.5a,d}/10\mu g/m^3) \quad (3.3)$$

Where Y_0 is the population's baseline mortality rate, RR is the Relative Risk of increased premature all-cause mortality per 10 $\mu g/m^3$ increase in outdoor PM_{2.5} concentration, and $\Delta PM_{2.5a,d}$ is the difference in equivalent annual outdoor PM_{2.5} concentration after adaptation on day d.

As in our prior work [7], Y_0 varies by grid cell and year (2000, 2050, 2100) using start-of-century values from the environmental Benefits Mapping and Analysis Program community edition (BenMAP-CE), and projected using International Futures, with details in Table A.9. RR is 1.14 [55]. We calculate $\Delta PM_{2.5a,d}$ with equation 3.4.

$$\Delta PM_{2.5a,d} = PM_{2.5a} - PM'_{2.5a,d} \quad (3.4)$$

Where $PM_{2.5a}$ is the annual mean outdoor concentration of PM_{2.5} with no adaptation, and $PM'_{2.5a,d}$ is the annual mean outdoor equivalent concentration of PM_{2.5} after adaptation

on day d. We calculate $PM_{2.5_a}$ with equation 3.5.

$$PM_{2.5_a} = \frac{\sum_{n=1}^{365} PM_{2.5_n}}{365} \quad (3.5)$$

Where $PM_{2.5_n}$ is the 24-hour mean outdoor concentration of $PM_{2.5}$ on each non-adaptation day n of the 365 days in year a.

We calculate $PM'_{2.5_{a,d}}$ with equation 3.6.

$$PM'_{2.5_{a,d}} = \frac{\sum_{n=1}^{364} PM_{2.5_n} + \psi \times PM_{2.5_d}}{365} \quad (3.6)$$

Where $PM_{2.5_n}$ is the 24-hour mean outdoor $PM_{2.5}$ concentration on each non-adaptation day n, and $PM_{2.5_d}$ is the 24-hour mean outdoor $PM_{2.5}$ concentration on the adaptation day d. ψ is the ratio of exposure to outdoor $PM_{2.5}$ when adapting (i.e., spending all day indoors) compared to not adapting (i.e., spending some of the day outdoors) given by equation 3.7.

$$\psi = \frac{24 \times F_{INF}}{T_{out} + (24 - T_{out}) \times F_{INF}} \quad (3.7)$$

Where T_{out} is the average daily time normally spent outdoors in hours, and F_{INF} is the infiltration factor. ψ thus quantifies the exposure reduction achieved by adapting, while accounting for exposure to outdoor $PM_{2.5}$ while indoors. We use a T_{out} of 1 hour based on the American Time Use Survey (ATUS) [123] and to ease comparison with previous studies [17]. We therefore assume that non-adapters spend 23 hours indoors. We use an F_{INF} value of 0.2 for this study based on surveys of the U.S. housing stock in [124] and

[125].

3.4.5 Adaptation Costs

We calculate adaptation costs, C_d , with equation 3.8.

$$C_d = \phi \times \xi \times T_{adapt} \quad (3.8)$$

Where ϕ represents the hourly adaptation cost, ξ is the portion of outdoor time given up for adaptation, and T_{out} is the time spent outdoors on a non-adaptation day. For all strategies, the default hourly adaptation cost for a grid cell is that grid cell's mean hourly wage, aggregated from county level U.S. census data.

3.4.6 Adaptation Decision-Making Strategies

We use these benefits and costs to study the effectiveness of short-term avoidance adaptation in reducing outdoor PM_{2.5}-related premature mortality risk. We estimate adaptation behavior with four models: Rational Actor, Threshold, Forced, and Social Learning. These strategies determine the number of days of adaptation (d) and non-adaptation (n).

Rational Actor

Our Rational Actor model represents an adult population acting with perfect information to adapt on any day with positive net benefits. We model this for each grid cell by sorting days of the year by decreasing marginal benefits of adapting that day. This uses equation

3.2 for all days in a year sorted from most to least polluted. The marginal costs of adapting an additional day are always given by equation 3.8 with $\xi = 1$. We then calculate NB_d with equation 3.1. All days with $NB_d \geq 0$ are adaptation days; once $NB_d < 0$, adaptation stops for all less polluted days, with NB_d , B_d , and C_d set to zero.

Threshold

Our Threshold model is based on current adaptation guidance, during which alerts are triggered by the AQI. We use thresholds of $AQI > 100$ and $AQI > 150$. This population of compliant adults adapts if the AQI in their grid cell exceeds the threshold, accruing costs (per equation 3.8 with $\xi = 1$) and benefits (per equation 3.2). We compare compliance levels at current rates (20%) to that of a theoretically fully compliant population.

Forced

Our Forced model considers the reference climate change scenario (REF), and requires the full adult population to reduce their exposures to those in our climate change mitigation scenario (P3.7). This population acts like our Rational Actors if they were willing – irrationally – to continue adapting beyond the point that benefits exceed costs, stopping only when their resulting annual mean $PM_{2.5}$ concentrations (per Equation 3.6 in their grid reach those of the annual mean outdoor concentrations of P3.7 (per Equation 3.6).

Social Learning

In the Social Learning model, populations are partitioned into adapters and non-adapters. At each model time-step, adapters and non-adapters decide whether to switch groups based on the relative utility of their two strategies. Like the Threshold model, those in the adapter group adapt when the $\text{PM}_{2.5}$ -based AQI in their grid cell is greater than the study threshold (either 100 or 150). NB_a is calculated by summing NB_d , B_d , and C_d for the proportion of the population that adapted.

Over time, the proportion of adapters is governed by the discrete social learning model, advancing by time-steps of one quarter, or 3-month period, to account for seasonal variation in pollution. This is calculated via Equation 3.9

$$\tilde{x}_{i_{t+1}} = x_{i_t} + \kappa_r \times \sigma_i \times (1 - x_{i_t}) \times \Delta U_{i_t} \quad (3.9)$$

Where x_{i_t} is the proportion of adapters in grid cell i at time t, $\tilde{x}_{i_{t+1}}$ is the proportion of adapters at the next time step, bound between 0 and 1, ΔU_{i_t} is the difference in utility between adaptation and non-adaptation (in SI). κ_r denotes the social learning rate in each U.S. census region, and σ_i is the population of grid cell i. Population is included because higher population areas lead to more diverse social networks for inhabitants which increases the spread of information [126]. The proportion of adapters in a grid cell is bound between 0 (no adapters in the population) and 1 (the entire population adapts), where the tilde above x in Equation 3.9 reflects this bounding.

We calculate ΔU_{i_t} in Equation 3.10.

$$\Delta U_{i_t} = \frac{R_{i_t} - C_{i_t}}{R_0} + \delta_r(2\omega(x_{i_t}) - 1) \quad (3.10)$$

Where C_i represents the cost associated with adaptation in grid cell i . R_i is a function that represents the perceived risk of negative health effects due to air pollution in region i . An adapter believes they mitigate their risk of these negative health effects by adapting, whereas a non-adapter receives the full amount of this perceived health risk. δ_r represents the weight of social norms in each U.S. census region and $\omega(x_i)$ is a function that determines the social norm that is predominant for grid cell i . R_0 normalizes the level of perceived utility from individual action to a similar magnitude as the influence of social norms. Cost has the same form as Equation 3.8, but summed over four months, and with ξ fit empirically and varying by U.S. census. This model is fit to representative surveys of U.S. adaptation [5], aggregated by U.S. Census region, from 2014-2020 with adjusted R^2 for the four regions ranging between 0.56 and 0.80.

3.4.7 Social Learning Model

Overview

Our social learning model represents the spread of adaptation behavior through a population by comparison of the utility between adapters and non-adapters. In this model, we define separate regions, i , which represent one 2 x 2.5-degree grid cell. Each region has a homogeneous population of fixed size at each time step. Individuals in this population

can either be adapters or non-adapters. We define the proportion of adapters as x_i , thus $1 - x_i$ is the proportion of non-adapters. In this population, social norms encourage the dominant behavior. The utilities of being adapters and non-adapters are:

$$U_{A_i} = -C_i + \delta_r \omega(x_i) \quad (3.11)$$

$$U_{N_i} = -R_i + \delta_r (1 - \omega(x_i)) \quad (3.12)$$

In these equations, C_i represents the cost associated with adaptation in region i . R_i is a function that represents the perceived risk of negative health effects due to air pollution in region i . An adapter believes they mitigate their risk of these negative health effects by adapting, whereas a non-adapter receives the full amount of this perceived health risk. δ_r represents the weight of social norms in each U.S census region and $\omega(x_i)$ is a function that determines the social norm that is predominant for grid cell i .

We subtract $U_{A_i} - U_{N_i}$ to define ΔU_i as:

$$\Delta U_{i_t} = -C_{i_t} + R_{i_t} + \delta_r (2\omega(x_{i_t}) - 1) \quad (3.13)$$

Where the parameters remain as defined in Equations 3.11 and 3.12. Since C_i and R_i are measured in dollars and take on large values of magnitude much greater than 1, they will be scaled to be unitless and close to the range of $[-1, 1]$, which is a similar order of magnitude for the social norms term. We do so by dividing the difference between R_{i_t} and

C_{i_t} by an empirically fitted constant, R_0 .

$$\Delta U_{i_t} = \frac{R_{i_t} - C_{i_t}}{R_0} + \delta_r(2\omega(x_{i_t}) - 1) \quad (3.14)$$

Where R_0 is an empirically fitted constant added to scale the difference between mitigated perceived risk and cost such that its influence is of similar magnitude to the influence of social norms.

In each grid cell, individuals will update their adaptation/non-adaptation decision based on the rate at which information is spread throughout their social networks, the proportion of the population who are currently adapters or non-adapters, and the difference in utility between the two strategies as calculated in Equation 3.14. The proportion of adapters in grid cell i at time $t+1$ is governed by the discrete social learning model (Equation 3.9) where one time step is equal to one quarter, or 3-month period.

The proportion of adapters in a grid cell must be between 0 (no adapters in the population) and 1 (the entire population is an adapter). Equation 3.15 enforces that bound.

$$x_{i_{t+1}} = \max(\min(x_{i_{t+1}}^{\sim}, 1), 0) \quad (3.15)$$

Determining Social Influence

In this model, we include the spread of information and influence across grid cells. We do this by defining $\omega(x_i)$, the social behavioral norm for grid cell i , as:

$$\omega_{x_{i_t}} = \sum_j SCI_{ij} x_{j_t} \quad (3.16)$$

Where $\sum_j SCI_{ij}$ is the normalized Social Connectedness Index (SCI) between two grid cells. SCI is defined by Meta/Facebook as the relative likelihood of a friendship link between users in two locations [127]. We use this as a proxy for information spread between two locations, which influences social norms. To calculate SCI_{ij} , we retrieved SCI values at the U.S. county-county level from Facebook. Then, we aggregated the county-county connections to the grid cell – grid cell level using the process introduced in [128]. The process begins by calculating the portion of counties that are in each grid cell. We then weight each county by its proportion of the total grid cell population. For each grid cell pair, we multiply county i – county j SCI values by the proportion of population that county i and county j make up. We sum these values to get the SCI between grid cells. Then, we multiply the SCI value between two grid cells by the population of both grid cells to get a relative number of connections between the grid cells. We then calculate the sum of the connections each grid cell has and normalize each grid cell connection total to determine the relative influence that each cell has on each other. The social norm for a grid cell is then calculated as the product of relative influence from grid cell to grid cell (SCI_{ij}) and the proportion of adapters in each influencing grid cell x_j .

Calculating Marginal Costs

Marginal costs within the Social Learning Model are calculated similarly to the Rational Actor Model. As most literature surveys show that curtailing outdoor activities is the predominant adaptation strategy in the general population, we set the cost of adaptation to be proportional to the reduction of time spent outdoors by adapters. We value lost time outdoors at the average wage rate. The cost of adaptation can be represented as:

$$C_{i_t} = \phi_i \times T_{adapt} \quad (3.17)$$

$$C_{i_t} = \phi_i \times \xi_i \times T_{out} \quad (3.18)$$

Where ϕ_i is the mean hourly wage rate in grid cell i . ξ_i is the proportion of an air quality alert day that an adapter chooses to spend indoors and is empirically fit by U.S. census region. ρ_i is the proportion of PM_{2.5} – driven air quality alert days within grid cell i over the current time period. T_{out} is the national average time spent outdoors, which is 1 hour per day over 365 days per year.

Calculating Perceived Risk

The perceived risk function R_{i_t} includes a term for likelihood of risk, which is a function of the proportion of bad air days in the current time step, ρ_{i_t} , a term for severity of risk, M_{i_t} and a scaling factor s .

$$R_{i_t} = s \times \rho_{i_t} \times M_{i_t} \quad (3.19)$$

The term for the severity of risk is based on $M_{it}^\sim$, which is defined as the annual per-capita costed premature mortality burden due to PM_{2.5}, which is updated at quarterly intervals.

$$M_{it} = VSL \times (1 - (1 - \eta_{it})x_{it})M_{it}^\sim \quad (3.20)$$

The costed premature mortality burden experienced by a grid cell of adapters and non-adapters is dependent on several factors. First is VSL, the Value of a Statistical Life, which is based on a population's willingness to pay to reduce their risk of premature death. Second is η_{it} , which is the proportion by which adapters reduce their PM_{2.5} exposure across the time period by adapting. Third is x_{it} , the proportion of the population who are adapters in the current time period. Last is $M_{it}^\sim$, which is the incidence of PM-driven premature mortality for a population of non-adapters.

The adaptation strategy for adapters is to reduce their time outdoors on days with an AQI > 100. The proportion of days with AQI > 100 also termed "Air Quality Alert Days" in each grid cell/time period is ρ_{it} . AQI > 100 is the threshold for "Unhealthy for Sensitive Groups" and is the point where the U.S. EPA begins recommending behavior change. When projected AQI exceeds this threshold, health ministries may generate an alert to people living nearby. Therefore, the term η_{it} is calculated as:

$$\eta_{it} = \frac{\sum_{d=1}^{365 \times \rho_{it}} \psi \times PM[PM > 35.4](d) + \sum_{d=1}^{365 - 365 \times \rho_{it}} PM[PM \leq 35.4](d)}{\sum_{d=1}^{365} PM(d)} \quad (3.21)$$

Where, similarly to the Rational Actor Model, the term ψ is the ratio of the exposure an adapter would experience when staying indoors on an alert day to the exposure one has

when they do not stay indoors. This term is dependent on ξ_i and F_{INF} and is defined as:

$$\psi_i = \frac{\frac{T_{in,day} + \xi T_{out,day}}{24} \times F_{INF} + \frac{(1-\xi_i)T_{out,day}}{24}}{\frac{T_{in,day}}{24} \times F_{INF} + \frac{T_{out,day}}{24}} \quad (3.22)$$

PM is the set of daily 24-hour mean $PM_{2.5}$ concentrations over a given year. The set is separated into two subsets, one that includes the $PM_{2.5}$ concentrations above $35.4 \mu g/m^3$ and one that is below or equal to $35.4 \mu g/m^3$. This distinction is made per the concentration values in Table A.1 as a $PM_{2.5}$ concentration of $35.4 \mu g/m^3$ corresponds with an AQI value of 100.

Fitting the Behavior Model

Fitting the parameters κ_r , δ_r , ξ_r , and R_0 was done by minimizing error between the census-region aggregated Social Learning Model and annual empirical values of adapters from the SummerStyles datasets. Equations 3.23, 3.24, and 3.25 were used to fit the behavioral model:

$$X_{r,t} = \sum_i p_i \mu_{i_r} x_{i_t} \quad (3.23)$$

$$X_{r_t} = \sum_i p_i \mu_{i_r} (\max(\min(x_{i_{t-1}} + \kappa_r x_{i_{t-1}}(1 - x_{i_{t-1}}) \Delta U_{i_{t-1}}(\xi_r \delta_r R_0), 1), 0) \quad (3.24)$$

$$\Delta U_i = \frac{R_i(\xi_r) - \beta_i(\xi_r)}{R_0} + \delta_r(2\omega(x_i) - 1) \quad (3.25)$$

Where r is one of the four U.S. census regions and μ_{i_r} represents the proportion of cell i in region r . We use a national, population-weighted hourly wage rate, ϕ , as we found that fitting using average wage by grid cell led to unrealistic results that were highly sensitive to grid-level wage values. Low-wage grid cells tended to equilibrate to full adaptation and high-wage grid cells tended to equilibrate to pure non-adapters within the fitting period of 2014-2020. Since adapters are updated quarterly and our data on adapters is yearly, X_r is interpolated to quarterly data. Also, throughout the fitting process, X_{r_0} are fit and allowed to vary by 25% of their empirical value.

3.4.8 PM_{2.5} Infiltration

The infiltration factor F_{INF} has been shown to be variable in previous studies. A national study by Persily et al. (2010) estimates that leakage accounts for a varying amount of infiltration based on the age and type of the dwelling unit [124]. Using 2015 U.S. Census American Community Survey data on housing age and the proportion of population living in single-family housing, we calculated the weighted average of ACH due to leakage across the country as approximately 0.33 [129]. Based on the plots by Long et al. (2001), an ACH rate of 0.33 corresponds with a $PM_{0.7-2.5}$ infiltration rate of approximately 20% [125]. We set $F_{INF} = 0.2$. Outdoor PM_{2.5} concentrations vary by climate policy, day, and grid cell, and are updated based on model outputs.

3.4.9 Time Use

We use an average daily time spent outdoors of one hour. To determine T_{out} , we reviewed the ATUS 2021 Activity Summary File, analyzing the data of each respondent, and the

location of their activity data according to the classification system developed by Hoehne et al. (2018) [130]. In their study, Hoehne et al. (2018) classified activities as occurring “Indoor”, “Outdoor”, or “Unknown” [130]. It is important to note that outdoor work is not accounted for in that study, leading to an underestimate of total outdoor time.

By applying these classifications to the ATUS 2021 data, we found that T_{out} – meaning activities classified as “Outdoor” – varied among respondents from 0 – 15.5 hours. The mean T_{out} value was 34 minutes per day. The mean time spent in “Unknown” locations was 45 minutes per day. This leads to a range of 34 – 79 minutes per day before accounting for outdoor work. Cox-Ganser and Henneberger (2021) reported that 14.5 million people worked jobs classified as outdoors in 2019 [131]. Based on the 2019 U.S. population of 328.3 million, this represents about 4.4% of the population. If we estimate that these people work 8 hours per day on 5 out of 7 days per week, this leads to an increase in the population-weighted average time spent outside of about 15 minutes per day, which brings the range of average time outside to 49 – 94 minutes per day.

To reduce the risk of being influenced too strongly by the COVID-19 pandemic, we also examined the ATUS 2019 Activity Summary File data [123]. That data showed a range of daily time spent outdoors of 0 – 17 hours. The mean time outdoors value was 29 minutes per day and the mean unknown time was 52 minutes per day. After accounting for the population who works outdoors, the range of average time spent outside would be between 44 – 96 minutes a day.

3.5 Results

3.5.1 Increasing Air Quality Alerts Under Climate Change

We find that, without reductions in emissions (of greenhouse gases or air pollutants), days with air quality alerts could quadruple on average by 2100 (Figure 3.1). The rise is steepest over the eastern U.S. – increasing by one month per year by 2100 – coinciding with areas with high Black populations, higher incomes, and leakier homes.

We emphasize that, within those areas, this unequal rise can lead to disparities in individual capacity to adapt to rising alerts. Leakier buildings let more air pollution inside, rendering adaptation less effective. Housing with poor indoor air quality could even make adaptation harmful. Further, living in leakier housing is correlated with lower incomes [105], reducing adaptive capacity for this vulnerable group.

This finding suggests that rising alerts could potentially place an undue burden on marginalized groups based on race and socioeconomic status. Note that we project future air pollution spatially, and project total population, income, and baseline death rates as in our prior work [7] (details in Appendix A), but rely on current demographics (specifying race but not Hispanic ethnicity), housing data, and time use. Those data derive from the U.S. Census Bureau [4], National Renewable Energy Lab [103], and Bureau of Labor Statistics [123], respectively. The ultimate distribution of impacts will depend on future patterns of pollution, demographics, housing, health, and activity.

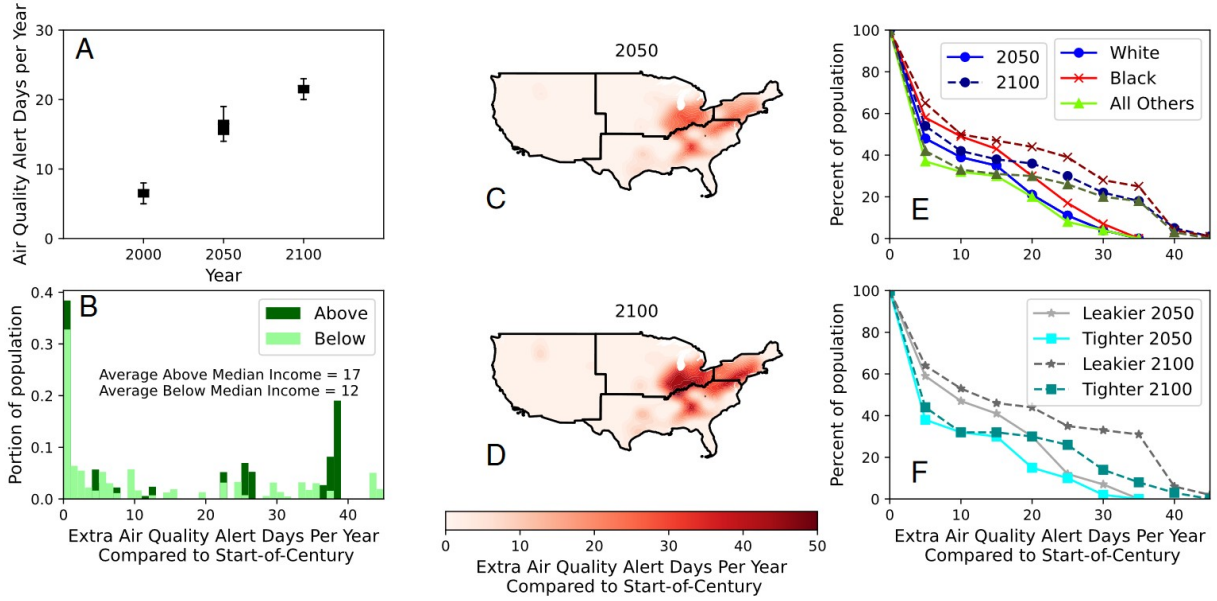


Figure 3.1: Air Quality Alert Days per Year (ADY) rise in the absence of emission reductions. All plots show air quality alerts (defined as outdoor fine particulate matter levels resulting in an Air Quality Index > 100) for the Reference (REF) climate change scenario. (a) National mean population weighted ADY for 2000, 2050, and 2100. Plots (b)-(f) show Extra ADY (EADY) compared to start-of-century (b) Histogram of EADY in 2100 for population above and below median income. (c/d) Spatial change in EADY in 2050 and 2100. (e) Cumulative density of EADY by race in 2050 and 2100. (f) Cumulative density of EADY by residential leakage rates above and below the national average. Leakage is defined as air changes per hour at a 50 Pa pressure difference (ACH50).

3.5.2 Benefits of Adaptation and Mitigation, and their Interaction

This increasing burden of air pollution caused by climate change could be addressed through adaptation or mitigation. We compare these strategies in Table 3.1. This table shows per capita benefits of reducing premature mortality risks achieved by reducing exposure to $\text{PM}_{2.5}$ of outdoor origin. That exposure reduction is achieved either via miti-

gation (here, reducing greenhouse gas emissions and thus reducing the worsening effect of climate change on air quality), adaptation (here, reducing exposures by moving indoors), or both.

For climate change mitigation levels, we compare a reference (REF) case with a global carbon pricing policy meeting the 2°C Paris Agreement target (P3.7). The reference case (REF) (also used in Figure 1) has a mean global surface temperature rise at end-of-century (ΔT) compared to the pre-industrial period (1850-1869) of 5.7°C. The climate policy (P3.7) has a ΔT of 1.9 °C. These scenarios are from our previous work, using models of the global economy and Earth system (33) (details in Section 3.4 and Appendix A).

Table 3.1 shows individual adaptation (by moving indoors) could offer benefits similar to – or even larger than – mitigation; however, those benefits of adaptation come with a significant burden. This is shown by comparing the benefits of “forced” adaptation to that of mitigation without additional adaptation: \$5,400 (\$490-\$15,000) and \$5,100 (\$460-\$14,000) population-weighted mean per-capita benefits, respectively. “Forced” adaptation requires the full adult population to fully compensate for its increased exposure, acting with perfect knowledge of its risks and benefits. Since we assume people only spend one hour per day outside, on average, across all outdoor activities (details in Methods), it would take an additional 142 days per year, on average, to achieve the same reduction in exposure afforded by climate change mitigation policy.

Table 1 also shows that the greatest benefit is achieved with both mitigation and adaptation (\$6,000 per person as the sum of benefits under P3.7). Their combination also tends to reduce the effectiveness of each strategy when used alone. Climate change

Table 3.1: Benefits of individual adaptation and climate change mitigation at end-of-century associated with reduced mortality risk from outdoor air pollution (PM_{2.5}). National population weighted mean per capita benefits in 2020 USD for multiple levels of mitigation and adaptation. Values in parenthesis represent 95% confidence interval in benefits related to health and economic uncertainty.

Mitigation Level	Adaptation Level	Adaptation Benefits (\$) (95% CI)	Mitigation Benefits (\$) (95% CI)
Low (REF)	None	\$0	\$0
	Rational	\$2,200 (200, 6100)	\$0
	Forced	\$5,400 (490, 15000)	\$0
High (P3.7)	None	\$0	\$5,100 (460, 14000)
	Rational	\$1,300 (120, 3600)	\$4,700 (430, 13000)

mitigation policy (P3.7) tends to reduce the need for adaptation. Under climate policy, per capita benefits of adapting drop from a mean of \$2,200 (\$200-\$6,100) to \$1,300 (\$120-\$3,600). The remaining \$1,300 benefit per person implies that, even under climate policy, there are gains to be made by boosting adaptation. Similarly, when estimating the benefits of mitigation, we find a small reduction in benefits due to adaptation. This interaction occurs because the adapters staying inside are less exposed to outdoor air, so receive less benefit from improving outdoor air quality. This effect reduces per capita benefits of mitigation, however slightly, from \$5,400 (\$490-\$15,000) to \$4,700 (\$430-\$13,000).

3.5.3 Adaptation Responses to Air Quality Alerts Under Climate Change

If air quality worsens, the burden of air pollution will rise, either in terms of higher health risks, or higher adaptation costs. In Table 3.2, we examine a range of possible adaptation behaviors to explore how protective individual adaptation might be. We evaluate our reference climate change scenario at end-of-century. We present uncertainty in the health and economic benefits of adapting derived from our prior work using 5000 Monte Carlo simulations in the U.S. Environmental Protection Agency (EPA) health impact software, the environmental Benefits Mapping and Analysis Program Community Edition (BenMAP-CE) [7, 69]. Uncertainty in costs is addressed later.

We first consider that there may be no additional adaptation, offering no protection at no cost – a common assumption in most studies of the future health impacts of air pollution. Next, we evaluate current practice (“Threshold”), which issues alerts to the general population when the AQI exceeds 150, and to the sensitive population when AQI exceeds 100. Here, we estimate the AQI using only outdoor $\text{PM}_{2.5}$, and its respective thresholds of $55.4 \mu\text{g}/\text{m}^3$ and $35.4 \mu\text{g}/\text{m}^3$. We use the current number of Americans who adapt to air pollution, estimated to be near 20% [5]. The top 20% most exposed Americans experience five alert days per year (Figure A.2); we estimate this will grow by more than a month by 2100 (Figure 3.1(e)). If current adapters comply with rising alerts, this amounts to national mean benefits of \$210 (\$20 to \$580) per person per year by 2100. Removing costs, mean net benefits are \$100 per person per year by 2100. Lowering the threshold for alerts from an AQI of 150 to 100 – the value used for populations that are particularly

sensitive to air pollution – has little effect on mean net benefits of adaptation.

It also is possible that more people will begin to comply with alerts. We examine the potential rise in adaptation four ways: (1) “Social Learning” allowing people to learn compliance (2) full compliance of the adult population to all air quality alerts (meaning all adults stay indoors on alert days) (3) all adults maximize their net benefits (benefits – costs) of adapting, using perfect information (“Rational Actor”) (4) adults are forced to adapt until they reduce their exposures by the same amount as climate change mitigation (“Forced”). We present national population-weighted mean results, noting that the spatial distribution of adaptation net benefits is similar to the rise in alerts shown in Figure 3.1(d) for “Social Learning”, “Rational Actor”, and “Threshold (full compliance)”.

We first assess the potential rise in adaptation due to social learning. We use a model (“Social Learning”) allowing people to switch between compliance and non-compliance, based on their perceived benefits of doing so (details in Section 3.4 and Appendix A). Those perceived benefits vary with pollution, costs, and the behavior of others, allowing them to learn compliance (or non-compliance) from others, and adapt to changing environmental conditions and social norms. Those who comply will give up some fraction of their outdoor time during alerts.

We find this social learning process could lead to higher adaptation rates in the future, on average, tripling the mean net benefits of adapting over current practice. This suggests that, even absent new adaptation policy, social influence could affect adaptation rates.

Nonetheless, it appears likely that the net benefits of adaptation will remain small compared to those of mitigation (P3.7); in fact, forcing the benefits to match appears

detrimental. This is seen by comparing the net benefits of full compliance, rational behavior, and forced adaptation. Each approach increases the average benefits of adaptation, with full compliance offering similar benefits to rational behavior. Forcing the adult population to reduce its exposure to outdoor $\text{PM}_{2.5}$ to the same level as climate policy (P3.7) offers the most benefits, by requiring people to stay indoors on many days without alerts. Though this achieves per capita benefits \$5,400 (\$490-\$15,000) higher than our mitigation scenario (\$5,100), the costs are \$11,000 per person, meaning this approach is detrimental, incurring an average net loss of \$5,900 per person.

3.5.4 Policy Levers to Promote Adaptation

Policy to promote adaptation could potentially offer net benefits. Robust and equitable policy, however, should consider the uncertainty, individual variability, and distribution of net benefits. To support this, we present a sensitivity analysis of factors affecting the maximum achievable net benefits (using “Rational Actor” behavior) (see Figure 3.2).

Adaptation offers higher net benefits to those who live in polluted areas, who work and live in high quality buildings, and who regularly spend time outdoors but place a low value on this time. This result is shown by the variation of net benefits of adaptation in Figure 3.2(a)-(d): increasing with (a) concentration and (b) time outdoors, decreasing with (d) adaptation costs and (e) infiltration. We present variation in adaptation costs as the value of outdoor time based on variation in wages, and from economic studies of the value of outdoor recreation [3].

Additional adaptation cannot benefit those who never go outdoors, have leaky homes

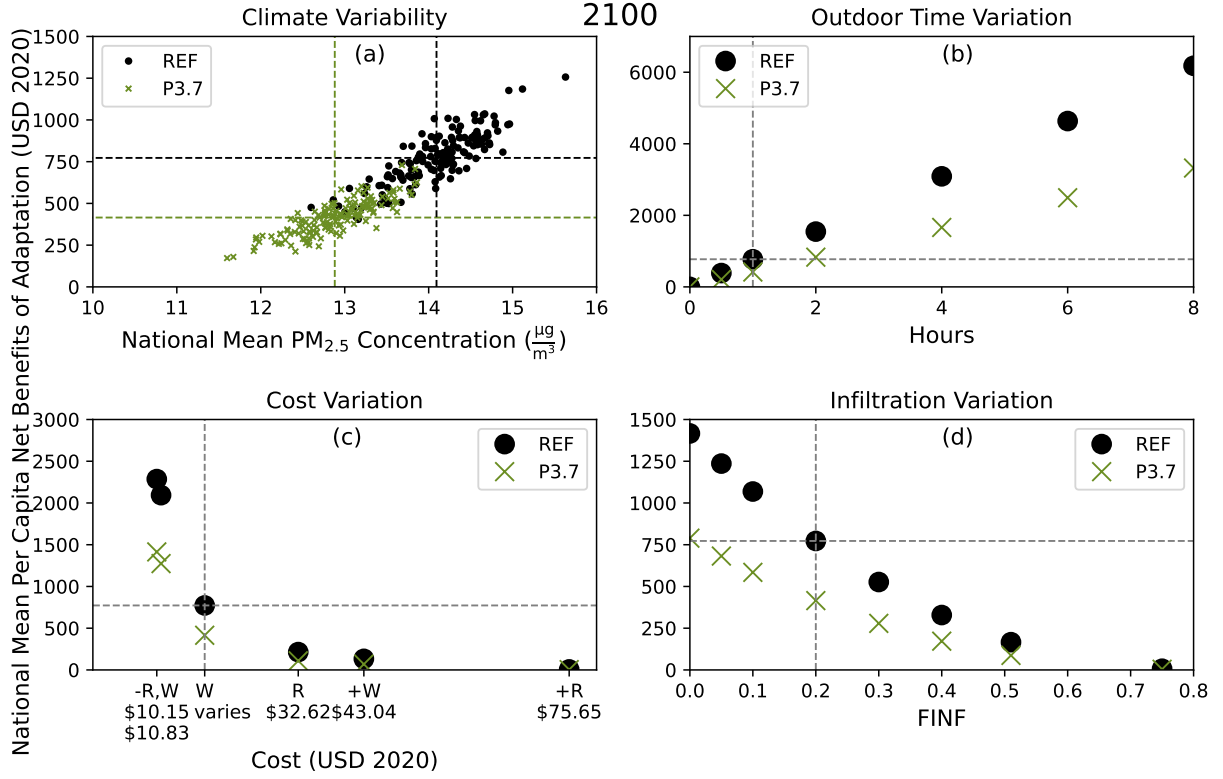


Figure 3.2: Variation of individual adaptation net benefits per capita under different levels of climate change mitigation in 2100 (in 2020 USD). (a) Scatter plot comparing national mean per capita net benefits of adaptation to national mean PM_{2.5} concentrations under REF and P3.7. Horizontal dashed lines represent population weighted mean per capita net benefits over an ensemble of 150 annual simulations representing end-of-century. Vertical dashed lines represent the corresponding mean population weighted PM_{2.5} concentrations. For (b)-(d), the vertical dashed lines represent the national mean of the dependent variable, and horizontal dashed lines show mean net benefits under REF. (b) Variation with amount of daily outdoor time given up. (c) Variation with cost per hour of adaptation. R represents costs derived from recreation values; W represents costs derived from wage values. – and + represent the minimum and maximum values applied nationally, respectively. R is the mean of all recreation values reported by Loomis (2005) [3]. W applies the wage for each grid cell aggregated from that grid cell’s corresponding county-level data [4]. (d) Variation with amount of outdoor pollution reaching indoors (as Infiltration Factor (F_{INF}))

($F_{\text{INF}} > 0.5$), or who highly value their outdoor time. A population with these characteristics may highly prefer mitigation to adaptation.

Mitigation reduces the need to adapt for all, and protects even those who cannot adapt. It also decreases variability in the benefits of adapting. This is seen by comparing the green (mitigation) to black (reference) cases for all subplots of Figure 3.2. Mitigation reduces annual mean $\text{PM}_{2.5}$ concentrations by $1.2 \mu\text{g}/\text{m}^3$, lowering the benefits of adapting. We saw this in Table 3.1, too, but Figure 3.2(a) shows that this holds well despite the variability in future annual mean concentrations. This means, too, that the rate of change of net benefits is smaller across all other variables in Figure 3.2.

To boost adaptation, policy can reduce adaptation costs, improve building quality, increase awareness, and should consider options for outdoor workers and people experiencing homelessness. We mention increasing awareness based on our social learning model; we showed that social learning could increase adaptation in Table 3.2. From Figure 3.2, we see the greatest gain in adaptation benefits is possible by minimizing adaptation costs, then reducing infiltration. This suggests policy levers including compensating people for moving indoors, and improving access to clean air. For most Americans, who live and work indoors, this could be achieved by improving indoor air quality. Figure 3.2 also shows that the highest possible gains from adaptation are for those who spend at least eight hours outdoors, a group consisting mainly of outdoor workers and people experiencing homelessness, each of whom require specific interventions.

3.6 Discussion and Conclusions

Climate change is known to raise risks to human health, increasing the need for adaptation to protect health [132]. We examine the potential effect of climate change on air quality alerts and adaptation by moving indoors. We find that unabated climate change triggers more air quality alerts guiding people to protect themselves by moving indoors, quadrupling on average by the end of this century. Those rising alerts could exacerbate existing racial inequalities and disparities in adaptive capacity. For example, we find alerts rise by one month per year in the Eastern U.S., in areas that currently have higher Black populations [4], and leakier homes that let more outdoor air pollution inside [103].

Boosting adaptation beyond current levels could offer net benefits, especially under worsening air quality, but even if Paris Climate Agreement targets are met. That policy could involve compensating people for moving indoors, improving building quality, and increasing awareness. Awareness could be raised through multimedia campaigns and communication channels targeted to relevant demographics [133, 111, 112], including, for example, integrating air quality messaging into patient charts [112].

For some, additional adaptation may be impossible, or even harmful, without appropriate intervention. It cannot benefit those who spend their time in leaky buildings ($F_{\text{INF}} > 0.5$), or who cannot give up their outside time, either because they do not go outside, because they value it highly, or because it is required for their work (true for approximately 4% of civilian workers [134]), or because they are experiencing homelessness (approximately 0.18% of the U.S. population [135]).

Thus, in order to effectively and equitably protect human health from air pollution,

policy for adaptation should be considered alongside mitigation. Mitigating climate change can reduce the increased risk from worsening air quality, and protects those who cannot adapt. Adaptation alone could pose an unrealistic substitute for improving air quality, in our case, requiring an additional 142 days per year of adaptation beyond current levels by 2100. At the same time, it remains highly uncertain how much climate change mitigation will be achieved, and how this will ultimately affect outdoor $\text{PM}_{2.5}$, meaning that enhanced adaptation may be needed [23].

Combinations of mitigation and adaptation should be evaluated and leveraged. We find the highest total benefits from both mitigation and adaptation, though the full distribution of costs and benefits must be assessed. We also find that their interaction reduces the effectiveness of each strategy alone. There remain other important feedbacks between air quality, climate change, and adaptation to unravel. Prior work has shown various effects of staying indoors on air pollution, including potential positive feedbacks of reduced traffic [136], negative feedbacks of increased heating and cooling demand (42), and feedbacks between climate change, cooling demand, and air pollution [137]. Some of these feedbacks can be leveraged to offer multiple benefits. For example, improving building quality to reduce infiltration and improve indoor air quality not only increases the benefits of adapting, it also reduces exposure to outdoor air pollution during all time indoors. It could also reduce energy demand for heating and cooling, with positive effects for climate change and outdoor air quality.

Our work is in line with prior estimates of the benefits of adapting to air pollution, given study differences. Buonocore et al. [17] find per capita benefits to be no higher than \$14 per person per hour in the population aged 65 and over in 2014-2017. Here,

we find an average benefit of \$31 per person per hour for adults aged 30 and over at the start-of-century across the U.S. The most important reason for this difference is that we account for the fact that people spend most of their time indoors, where exposure to $\text{PM}_{2.5}$ of outdoor origin is lower, therefore, exchanging one-hour outdoors for indoor time offers a greater reduction in overall exposure to $\text{PM}_{2.5}$ of outdoor origin. When we reproduce [17]’s findings with our estimate of infiltration, we find up to a 1.5-fold (or 50%) increase in benefits. We also do not include morbidity or ozone, but these reflect less than 10% of our benefits (see Table A.2).

In order to inform policy to protect health from outdoor air, we focus on $\text{PM}_{2.5}$ of outdoor origin. We represent the main risk-cost trade-offs in air quality policy analysis ($\text{PM}_{2.5}$ -associated premature death), existing adaptation guidance (via air quality alerts), and the current dominant adaptation mode (limiting time outdoors). We estimate the effects of climate change on air pollution, including anthropogenic and biogenic sources, but do not account for wildfires, which could also exacerbate air pollution under climate change [138], enhancing benefits of adaptation beyond our estimates. Focusing on outdoor $\text{PM}_{2.5}$ ignores $\text{PM}_{2.5}$ that originates indoors. For adaptation to be protective, individuals must be able to move indoors to relatively clean environments. Here, we conservatively estimate 20% infiltration of outdoor $\text{PM}_{2.5}$ indoors, while new U.S. homes may have infiltration factors as low as 1-2% [104]. Low-cost $\text{PM}_{2.5}$ filtration is available to the two-thirds of U.S. households using central air-conditioning [139]. However, indoor sources of $\text{PM}_{2.5}$, such as tobacco smoking, cooking, and the use of consumer products, may substantially increase indoor $\text{PM}_{2.5}$ concentrations [140, 141, 142], and could represent comparable exposures as outdoor sources [143, 144]. Further work is needed to understand how increased adaptation

to outdoor pollution could affect total $\text{PM}_{2.5}$ exposure and associated risks to human health. Similarly, significant shifts from outdoor to indoor activities could have multiple impacts to well-being not considered here, particularly if physical activity were affected. Current guidance from the American Thoracic Society is not to reduce physical activity in response to poor air quality, but to shift it to locations and times when pollution is lower [145]. Future work should consider the broader health implications of adaptation.

Our work contributes to challenges in nature-society systems modeling on cross-scale effects (e.g., time scales, scales of impact and action), representing social responses, and addressing uncertainty (53–55). We build on recent examples focusing on climate change, behavior, and social dynamics and the effects on mortality and policy outcomes (e.g., [7, 146, 147, 148]). We represent several approaches to modeling adaptation decisions to assess their effect on nature-society interactions [149]. This includes a simple model of social learning based on replicator dynamics, whose theory, behaviors, and applications in nature-society models we recently reviewed [150]. That model fits well to historical, nationally-representative surveys of adaptation behavior. However, other theories of behavior could also explain these data, beyond those explored here. Behavior could also evolve over time, e.g., due to changing risks, risk perception, activities, or valuation. We present ranges of net benefits of adaptation across physical and behavioral characteristics to inform more detailed demographic analysis and projection. Representing human behavior in nature-society systems models remains a frontier capability with much future work ahead [27].

Table 3.2: National population weighted per capita net benefits (2020 USD) in the adult population for various levels of adaptation to air pollution in the absence of climate change mitigation by end-of-century. Adaptation reflects the current dominant approach, which is to limit time outdoors. Adaptation levels are varied by changing the threshold for air quality advisories, compliance levels, and decision approaches. For benefits, values in parenthesis represent the 95% CI due to uncertainty in health and valuation. Note that uncertainty in costs is not included here, but is explored in 3.2.

Threshold for Air Quality Advisory	Compliance Level	Adaptation Cost (\$)	Adaptation Benefits (\$) (95% CI)	Adaptation Net Benefits (\$)
Current (AQI >150)	Current	\$110	\$210 (20, 580)	\$100
Lowered (AQI >100)	Current	\$340	\$440 (40, 1200)	\$100
Current (AQI >150)	Socially-influenced compliance	\$340	\$700 (60, 2000)	\$360
Lowered (AQI >100)	Socially-influenced compliance	\$1,200	\$1,700 (150, 4700)	\$480
Current (AQI >150)	Full compliance by adult population	\$550	\$1,000 (90, 2900)	\$500
Lowered (AQI >100)	Full compliance by adult population	\$1,700	\$2,200 (200, 6200)	\$530
Rational behavior	Maximum net ben- efits of adaptation	\$1,400	\$2,200 (200, 6100)	\$780
Forced	Forcing adaptation to same risk reduc- tion as mitigation	\$11,000	\$5,400 (490, 15000)	-\$5,900

Chapter 4

Future Ozone and PM_{2.5} in the US Under Varying Climate Policy: Air Quality Alerts, Health Impacts, and Adaptation Implications

The work in this chapter has been submitted for publication.

4.1 Abstract

Without emission reductions, climate change is expected to increase air pollution over much of the US, including extreme values of both ozone and PM_{2.5}. This may increase future air quality alerts and the need to adapt by moving indoors. Here, we use an Integrated Modeling Framework to estimate the Air Quality Index (AQI), which triggers alerts. We evaluate future ozone and PM_{2.5} concentrations under three levels of climate policy. We find that, without climate policy, 9 times as many people may experience mean AQI in the “Unhealthy for Sensitive Groups” category in 2100 compared to 2000. This leads to

a doubling in alerts nationally and a 250% increase in days where both ozone and $\text{PM}_{2.5}$ are above alert thresholds. Most future alerts are found to be caused by high levels of ozone, but the health-related economic burden of future air pollution is primarily (94%) caused by $\text{PM}_{2.5}$. Adapting by staying indoors reduces exposure to outdoor ozone by 5 times as much as $\text{PM}_{2.5}$ (30% vs 6%). The greater effectiveness of adapting to ozone, and greater harm caused by $\text{PM}_{2.5}$, mean that the health benefits of adapting to either pollutant are similar. The difference between population groups, however, is stark. Senior (65+) populations receive up to 75 times the benefits per day by eliminating their outdoor time as the lowest-risk group (age 18-35). The disproportionate impacts to this vulnerable group, nearly half of whom are already housebound, require more targeted messaging and guidance, especially as climate-related risks rise.

4.2 Introduction

Air pollution has repeatedly been shown to be harmful to human health. Increases in outdoor pollutant concentrations cause increased morbidity [151, 152] and premature mortality [153, 154] in exposed populations. In the US, the Air Quality Index (AQI) [6] reports the “level of concern” associated with different pollutant concentrations [6]. AQI is calculated individually for each pollutant. Then, the maximum value among pollutants is reported as a number between 0-500. AQI values are categorized with labels ranging from “Good” (0-50) to “Hazardous” (301-500) (Table B.1). When AQI values are above certain thresholds, typically 100 (“Unhealthy for Sensitive Groups”) or 150 (“Unhealthy”), alerts may be relayed to the public [16, 5]. Ozone and $\text{PM}_{2.5}$ are responsible for over 99% of AQI

alerts [18] and are thus the primary focus of this study.

Climate change is expected to make air pollution worse in the US [18, 155], an effect termed the “climate penalty”, but the resulting change in AQI alerts is not well known. Climate change is expected to increase drought [156], heat waves [157], and wildfires [158] over the 21st century. These factors all contribute to an expected increase in extreme outdoor ozone and PM_{2.5} concentrations [159, 160]. One such study projected that, even with some emission reductions to combat climate change, the non-compliance zone for areas exceeding the National Ambient Air Quality Standard (NAAQS) for ozone may expand by 8.5 million residents by mid-century [161]. However, we are aware of only one study to have evaluated these increases in terms of AQI changes, and they only considered one pollutant [162]. They found that days with AQI over 100 due to PM_{2.5} could quadruple by 2100 without emission reductions [162]. So, while conditions for air quality alerts are expected to change, the literature does not show how the population experiencing alerts may grow, and what their health-related impacts might be.

Air pollution can be reduced through climate policy [7] and local [12] air quality policy, but decisions to enact this policy are beyond most people’s control. Other pollution sources, like forest fires [158] and trans-boundary pollution [163], are difficult to control, even for air quality managers. Yet, there is demand for air pollution exposure reduction, as a recent study on over 4,000 US adults found that 90% of respondents believe that air pollution harms human health [97].

To address their individual risk, then, people rely on independent adaptation, as recommended by AQI messaging. When informed that air quality is bad, 57% of respondents

of a nationally representative survey reported changing their behavior [97]. As 36.5% of people thought that air quality was bad, this means that approximately 21% of the population adapts to air pollution [97]. This is higher than a previously reported value of 15% [5]. The most common behavior change in response to poor air quality was spending less time outdoors [5, 97], which we term “avoidance adaptation”. Other strategies to reduce exposure, though not mentioned with standard AQI guidance, include improving building mechanical system filtration [108, 104], wearing masks [98], and using portable filtration devices [164].

The AQI, developed by the US Environmental Protection Agency (EPA), is designed to assess compliance with regulations, not to quantify risk [165]. The NAAQS for ozone and $\text{PM}_{2.5}$ are the threshold for AQI values of 100, or “Unhealthy for Sensitive Groups” [6]. While there is some alignment between health risk and NAAQS concentration standards, previous studies have found that the single pollutant method of calculating AQI is an adequate proxy under simple pollution patterns, but is not well associated with risk under more complex mixtures [88]. A study on hospital admissions in New York also found that a single pollutant may not be enough to communicate the health risks associated with air pollution [89]. Other countries, such as Canada, have moved to a multi-pollutant index based on excess mortality risk [14] that is well associated with both mortality and morbidity outcomes [15].

There is limited research on how effective AQI guidelines are at promoting beneficial adaptation. A recent review rated the strength of evidence supporting six recommended behavior changes to reduce ambient air pollution exposure, and found it “lacking” [26]. A study on how AQI recommendations can lead to reductions in heart disease had to “make

plausible estimates of the 24-hour exposure reduction incurred by following the activity guidance” due to the lack of quantitative values [99]. Buonocore et al. (2021) modeled adaptation by removing exposure to the highest waking hour of outdoor concentration in the over-65 population across three U.S. cities [17]. Sparks et al. (2024) incorporated ambient pollution exposure in both indoor and outdoor environments, but did so in a simplified way, and only for PM_{2.5} [162].

Adaptation in the over 65 (senior) population is especially important because they experience most of the health impacts of air pollution [166]. Both PM_{2.5} and ozone exposure have been significantly associated with increased risk of mortality for older adults, even at concentrations below NAAQS standards [167]. Populations are aging [168], which is expected to amplify effects of the climate penalty [169]. The elderly are part of the “sensitive groups” who are advised to take protective actions at lower pollution levels (AQI > 100) than the general population (AQI > 150) [6]. However, seniors are special group that may merit different thresholds, communication strategies, and advice. They may require different thresholds because their mortality risks are generally higher than their younger peers in sensitive groups. They receive information differently than their juniors, with most (85%) learning of air quality alerts via television, and between 34% and 50% receive alerts via newspaper [16]. Finally, they may need specialized guidance, as they spend less time outside, on average, with 47% spending no time outside (based on our analysis of American Time Use Survey Data [170] from 2008 to 2023).

Risks to seniors are important to understand as a growing group. Future increases in pollution concentrations can be especially harmful as more people in the U.S. are expected to enter the “Sensitive Groups” demographic through the 21st century. Between

2012 and 2050, the U.S. population over 65 is expected to increase from 43 million to 80 million, or 12% of the population to over 20% [168]. The Over 65 population share reaches 30% in every SSP scenario studied in Yang et al. (2022) which will substantially increase PM_{2.5}-driven mortalities unless concurrent reductions in baseline mortality rates occur [171]. The increasing health burden for an aging population can be seen in China, where pollution-related mortalities have remained steady due to population aging largely offsetting decreases in ambient concentrations [172, 173]. Better understanding the risks to this growing, vulnerable group could thus inform new, effective strategies to protect their health.

In this study, we investigate how AQI mean values and alerts change through the 21st century under different climate futures. We identify which pollutants are responsible for changes in AQI alerts and which contribute most to health impacts. We improve upon previous adaptation studies by providing simple, quantified estimates of ozone and PM_{2.5} exposure reduction due to avoidance adaptation. We compare the benefits of adaptation when responding to ozone or PM_{2.5} driven AQI alerts and identify how much of the future economic health burden can be offset by adaptation. Lastly, we quantify how the benefits of adapting vary with age. This work will identify the size and makeup of populations at increased risk for air quality alerts, and inform targeted thresholds and messaging more closely aligned with individual risk.

4.3 Methods

4.3.1 Modeling Future Concentrations

This study uses modeled future ozone and PM_{2.5} concentrations reported and evaluated in previous work [7, 20, 121]. Those prior studies used the Massachusetts Institute of Technology (MIT) Integrated Global System Model (IGSM) framework [8]. The MIT IGSM framework links three models: a global computable general equilibrium economic model (EPPA), an earth system model of intermediate complexity (MESM), and an air quality model (CAM-Chem). It was used to model air pollution concentrations for ozone and PM_{2.5} at three target years (2000, 2050, 2100) for three policy scenarios: a reference scenario with no climate policy enacted (REF), a scenario where global warming is limited to 2.5 °C above pre-industrial (2.5C), and a scenario where global warming is limited to 2 °C (2C). The mean air quality for each target year was simulated using three decades and five initializations of the climate (details in Paltsev et al, 2015) [8]. Anthropogenic pollutant emissions are held constant with start-of-century values in all scenarios to isolate the effect of climate change on ambient pollutant concentrations. Modeled ozone concentrations have been bias-corrected so that one year return ozone concentrations are on average 3 ppb lower than measured values [161]. Modeled national population-weighted mean PM_{2.5} concentrations are within 7% of measured values [121]. Projected concentrations of ozone and PM_{2.5} also agree well with similar studies using different models [7]. We limit analysis to May 1st through September 30th of each year to align with the peak ozone season.

4.3.2 Calculating AQI Values

AQI values are calculated for modeled ozone and PM_{2.5} data following U.S. EPA methodology. Ozone and PM_{2.5} have concentration breakpoints for each AQI category (Table B.1). Between each breakpoint, the AQI value for a given pollutant p (I_p) is calculated based on Equation 4.1, adapted from the EPA’s Technical Guidelines for AQI [6].

$$I_p = \frac{I_{Hi} - I_{Lo}}{BP_{Hi} - BP_{Lo}} (C_p - BP_{Lo}) + I_{Lo} \quad (4.1)$$

Where C_p is the concentration of pollutant p (24-hour mean concentration in $\mu g/m^3$ for PM_{2.5} and daily 8-hour maximum in ppm for ozone), BP_{Hi} is the concentration breakpoint greater than or equal to C_p , BP_{Lo} is the concentration breakpoint that is less than or equal to C_p , and I_{Hi} and I_{Lo} are the AQI values corresponding to BP_{Hi} and BP_{Lo} respectively.

4.4 Calculating Health Impacts Due to Changes in Air Pollution Exposure

We used BenMAP-CE v1.5 [69] to estimate the health effects of air pollution changes, following U.S. EPA regulatory analysis standards. The general form of the equation to calculate the change in health outcomes (ΔY) is shown in Equation 4.2.

$$\Delta Y = Y_0 \times Pop \times (1 - \exp(-\beta \times \Delta C_p)) \quad (4.2)$$

Where Y_0 is the baseline incidence rate of a given outcome, Pop is the affected population, β is the risk coefficient, and ΔC_p is the change in pollutant concentration between two scenarios.

We employed different health impact functions (Equation 4.2) to represent morbidity and mortality, each with their own value of β . Details about the studies and pooling are included in Table B.2. We examined different age ranges within the population (Under 18, 18-35, 36-64, and 65 and over), through data provided by BenMAP-CE. BenMAP-CE provided the population data partitioned by age range, which gave the number of people in each group and grid cell (Pop). Y_0 varied by population group for mortality. We used two types of comparisons to find differences in pollutant concentrations. First, we compared future years to modeled historical years under baseline behavior. Second, we compared adaptation behavior to regular behavior for a given target year. Each of these are explained in the following sections.

4.4.1 Valuing Changes in Health Burden

We valued the change in health outcomes by multiplying the change in health outcomes by the cost of incurring that health outcome (Equation 4.3).

$$\Delta B = \sum_i C_i \times \Delta Y_i \quad (4.3)$$

Where ΔB is the change in economic health burden, C_i is the cost associated with health outcome i and ΔY_i is the change in incidences of health outcome i . We specify the cost

of a health outcome in two ways, as recommended by the most recent EPA Guidelines for Preparing Economic Analyses [67]. We use the EPA’s preferred measure for damages and benefits [67], namely, willingness to pay (WTP) to reduce the risk of a health outcome. We use WTP in this study to determine the economic cost or benefit associated with changes in morbidity and premature mortality risk. To value the economic burden of premature mortality, we use the Value of a Statistical Life, which represents WTP extrapolated to a risk reduction of 1. We use the U.S. EPA’s recommended VSL value of \$8.7 million (2015 USD) [174]. The second way to quantify C_i is to use the cost-of-illness (COI) of treating an adverse health outcome. COI estimates are provided by the U.S. EPA [174]. Valuation methods for each morbidity and mortality outcome are presented in Table B.2. When calculating future health impacts, we change concentrations only, keeping the population (Pop), baseline risks (Y_0) and costs (VSL or COI) constant. This is designed to isolate the effects of concentration. In practice, modeled future concentrations are generated by future populations in future economies and are usually analyzed as such. However, this approach conflates changes in pollution concentrations, population characteristics, and economic growth[171]. For this work, we isolated the effect of atmospheric composition changes on health impacts and valuation. We name the different pollution concentrations produced by different future climate policy scenarios “Counterfactuals” to reinforce that these are only pollution differences, not full scenario differences.

4.4.2 Quantifying Exposure Reduction from Adaptation

A person's daily exposure E_{d_p} to an ambient air pollutant p is calculated using Equation 4.4:

$$E_{d_p} = \sum_m L_m \times I_m \times F_{INFm_p} \times C_p \quad (4.4)$$

Where L_m is the location fraction, or the fraction of one's time spent in microenvironment m , I_m is the ratio of the activity intensity that occurs in microenvironment m compared to the rest of the day, F_{INFm_p} is the infiltration factor, or ratio of indoor pollution to outdoor pollution for a given pollutant p in microenvironment m , and C_p is the outdoor concentration of pollutant p . Equation 4.4 is similar to the microenvironment exposure model used in prior studies of total exposure to air pollution [108, 144].

To determine location fraction L_m , we split people's time into four different microenvironments in this study: Residential, Commercial, Vehicle, and Outdoor. We used American Time Use Survey (ATUS) data from 2008 – 2019 to identify the portion of time that people spend in each microenvironment (Location Fraction) in a similar way to Hoehne et al. (2018)[130]. We calculate activity intensity by assigning a metabolic equivalent value (MET) to ATUS data, as was done in Tudor-Locke et al. (2011)[175]. To determine the average activity intensity in each microenvironment I_m , we use the ratio of the average MET value in each microenvironment to the daily average MET value. We determine the fraction of outdoor pollution that enters indoors (infiltration factor, or F_{INF}) based on previous literature[176, 177, 178, 179, 124, 180, 181]. For $PM_{2.5}$, we determined Residential

F_{INF} using NREL ResStock air changes per hour (ACH) values. The conversion is shown in Equation 4.5 below:

$$F_{INF} = \frac{P \times ACH}{ACH + \beta} \quad (4.5)$$

Where P is the fraction of $PM_{2.5}$ that penetrates the building envelope (0.73, Zhao and Stephens [182]), ACH is the national average air changes per hour based on ResStock data, and β is the settling velocity of $PM_{2.5}$. Commercial and vehicle F_{INF} values were gathered from previous studies [180, 181]. The outdoor F_{INF} is 1, as there is no protection from outdoor pollution while outside.

For ozone, previous studies use indoor-outdoor ratio (I/O) as a proxy for F_{INF} because indoor generation is low [176, 177]. We derive F_{INF} values for each microenvironment from Lai et al. (2015), who measured ozone I/O via different mechanisms. They found a I/O of 0.09 for infiltration, which is representative of the residential and vehicle microenvironments. For commercial, we used their mechanical ventilation value of 0.19. These values are within the range found in other previous studies [183].

We used national average values for all exposure parameters. These values of all parameters on typical non-adaptation and adaptation days are presented in Tables 4.1 and 4.2.

We defined adaptation as shifting all time in the Outside microenvironment to the Residential microenvironment. This leads to changes in the location fraction and activity intensity ratio values, which lead to a new (reduced) personal daily exposure E'_{dp} . E'_{dp} is calculated using Equation 4.6, which is like Equation 4.6 used for E_{dp} .

Table 4.1: Fraction of time spent, activity intensity ratio, and infiltration factors for ozone and PM_{2.5} on a typical non-adaptation day. Location fraction values are based on national average from American Time Use Survey data.

Microenvironment	Location Fraction (L_m)	Fraction	MET Ratio (I_m)	F_{INF} Ozone	$F_{INF}PM_{2.5}$
Residential	0.718		0.923	0.09	0.45
Commercial	0.197		1.032	0.19	0.35
Vehicle	0.057		1.341	0.09	0.6
Outdoors	0.028		1.853	1	1

$$E'_{d_p} = \sum_m L'_m \times I'_m \times F_{INF_{m_p}} \times C_p \quad (4.6)$$

Adaptation turned the Location Fraction L'_m value for Outside 0 and added that time to Residential. We kept the activity intensity for the shifted activity the same, such that adaptation does not reduce physical activity, as suggested by the American Thoracic Society [145]. This increased the MET Ratio I'_m for the Residential microenvironment. The infiltration factors (F_{INF}) remained the same between non-adaptation and adaptation days. Location Fraction, MET Ratio, and infiltration factors under adaptation are shown in Table 4.2.

Table 4.2: Fraction of time spent, activity intensity ratio, and infiltration factors for ozone and PM_{2.5} on a typical adaptation day. Values are based on national average from American Time Use Survey data.

Microenvironment	Location tion (L_m)	Frac-	MET Ratio (I_m)	F_{INF} Ozone	$F_{INF}PM_{2.5}$
Residential	0.746		0.958	0.09	0.45
Commercial	0.197		1.032	0.19	0.35
Vehicle	0.057		1.341	0.09	0.6
Outdoors	0		0	1	1

4.4.3 Relating Changes in Exposure to Equivalent Changes in Outdoor Concentration

As shown in Equation 4.2, calculating health impacts through BenMAP-CE requires differences in outdoor concentrations (ΔC_p). We used Equations 4.7 through 4.10 to convert changes in exposure to changes in outdoor concentration for use in health impact functions to estimate health outcomes.

First, we defined the effectiveness of adapting to a given pollutant p as the ratio between E'_{dp} and E_{dp} . We defined this value as Ψ_p and formalize it in Equation 4.7.

$$\Psi_p = 1 - \frac{E'_{dp}}{E_{dp}} \quad (4.7)$$

Using the Location Fraction (L_m and L'_m), MET Ratio (I_m and I'_m), and infiltration factors (F_{INF} Ozone and F_{INF} PM_{2.5}) in Tables 4.1 and 4.2, we find $\Psi_{ozone} = 0.30$ and

$\Psi_{PM_{2.5}} = 0.06$. This means that it is much more protective, by almost a factor of 5, to adapt to ozone than to adapt to $PM_{2.5}$.

Over 153 days of smog season, we have n non-adaptation days and a adaptation days. We index non-adaptation days by j and adaptation days by k . We use $(1 - \Psi_p)$ to convert the outdoor concentration on a given adaptation day k (C_{p_k}) to a concentration that would give the equivalent exposure that one would have on a non-adaptation day (C'_{p_k}). This is shown in Equation 4.8.

$$C'_{p_k} = (1 - \Psi_p) \times C_{p_k} \quad (4.8)$$

Over the course of the summer smog season, we can aggregate the effects of individual adaptations to see how it affects average seasonal exposure. We do this through Equation 4.9.

$$C'_p = \frac{\sum_{j=1}^n C_{p_j} + \sum_{k=1}^a C'_{p_k}}{n + a} \quad (4.9)$$

Where C'_p is the equivalent seasonal average pollutant concentration after adaptation, C_{p_j} is the outdoor pollution concentration on non-adaptation days j , C'_{p_k} is the equivalent outdoor pollution concentration after adaptation, on adaptation days k , n is the number of non-adaptation days in the smog season, and a is the number of adaptation days in the smog season. Values for n and a are calculated based on local concentrations in each grid cell. We assume that populations adapt when their local AQI is higher than a selected threshold, simulating what we term an AQI alert. To calculate the maximum benefit from

adaptation, we assume everybody in a grid cell adapts on each “alert day”. While full compliance is unlikely [5, 97], we use it to test the full potential benefits of adaptation.

We calculate ΔC_p as the difference between C_p and C'_p as shown in Equation 4.10. This ΔC_p value is used in Equation 4.2 to calculate the health effects of adaptation.

$$\Delta C_p = C_p - C'_p \quad (4.10)$$

4.5 Results

Average AQI values over the summer smog season will increase throughout the country under the REF (no climate policy) scenario (Figure 4.1). In the start-of-century (REF 2000) case, 78% of the population has a mean AQI value within the “Moderate” AQI category. The remainder primarily enjoys “Good” air, while very few (4%) have mean air quality in the “Unhealthy for Sensitive Groups” category (Figure 4.1 (d)). At the start-of-century, the only geographic area that has a “Unhealthy for Sensitive Groups” average AQI is the greater Los Angeles area (Figure 4.1 (a)). This aligns with U.S. EPA Air Data measurements, where the mean smog season AQI is 128 for the Los Angeles-Long Beach-Anaheim CBSA (code 31080) between 1995-2005.

Under the mid-century (REF 2050) counterfactual, the mean smog season AQI values for two grid cells shift from the “Moderate” to “Unhealthy for Sensitive Groups” category. These grid cells, which include New York City and Pittsburgh, are the first in the Eastern part of the U.S. to reach this threshold (Figure 4.1 (b)). The greater Los Angeles area remains in the “Unhealthy for Sensitive Groups” category and the mean AQI values increase

from 114 in 2000 to 122 in 2050. There are very few areas that switch between the “Moderate” or “Good” AQI categories. The proportion of the total population under the REF 2050 counterfactual that has a mean smog season AQI value in the “Unhealthy for Sensitive Groups” category is 12% - triple that of REF 2000. The proportion of the population with a mean AQI value in the “Good” category slightly decreases to 16%. Consequently, the “Moderate” AQI fraction decreases to 72% (Figure 4.1 (d)).

In the end-of-century (REF 2100) counterfactual, the transition between mean smog season AQI values in the “Moderate” to “Unhealthy for Sensitive Groups” categories continues. Two more areas in southern California and 12 more across the Rust Belt/Midwest move from a mean smog-season AQI of “Moderate” to “Unhealthy for Sensitive Groups” (Figure 4.1 (c)). The grid cell encompassing Los Angeles maintains the highest mean AQI – reaching a mean value of 142 over smog season.

Worsening air quality in 2100 is evidenced by the number of people with mean values in each AQI category (Figure 4.1 (d)). In REF 2100, over 100,000,000 people, or 33% of the study population would have an average AQI value between May 1st and September 30th that is “Unhealthy for Sensitive Groups”. This means that more than a third of the U.S. population would see daily alerts recommending action for children, the elderly, and those with underlying health conditions. There is over a factor of nine increase in the number of people with mean AQI values in this category between REF 2000 and REF 2100 (11,856,405 vs 106,850,490). The percent of the population with mean AQI values in the “Good” category is steady at 16% and the proportion of people in the “Moderate” category decreased to 51%.

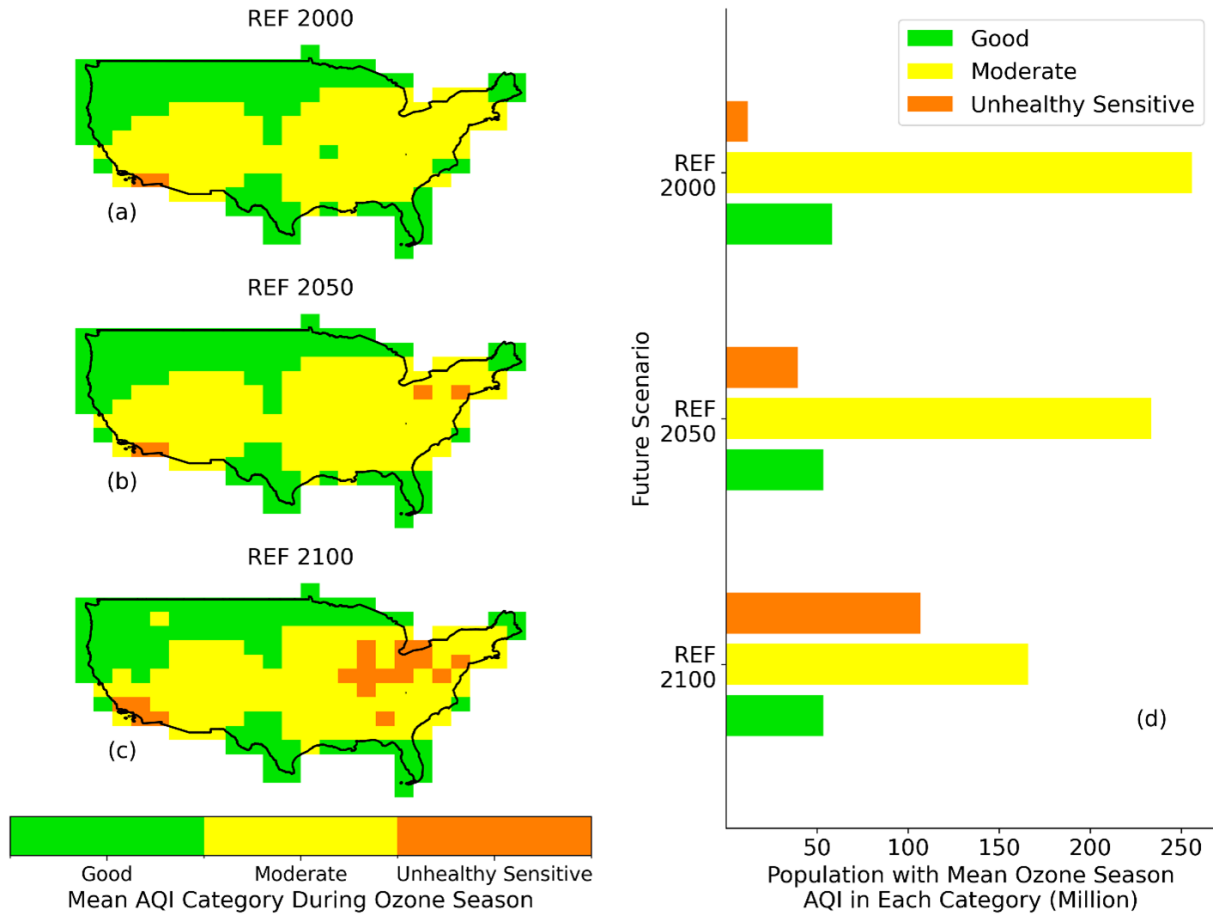


Figure 4.1: Average AQI over the summer smog season. Results are shown for the REF 2000 (a), REF 2050 (b), and REF 2100 (c) counterfactual concentration scenarios. Subplot (d) shows the number of people experiencing a mean smog season (May 1st – September 30th) AQI in the “Good”, “Moderate”, or “Unhealthy for Sensitive Groups” categories.

Episodes of high air pollution during the smog season are projected to affect more people for longer periods of time if we do not reduce emissions (Figure 4.2). Figure 4.2 shows the population-weighted likelihood of an alert under the REF counterfactual for the years 2000, 2050, and 2100. That likelihood is calculated as the proportion of days on which ozone, $PM_{2.5}$, or both pollutants exceed their AQI thresholds, over 150 annual

simulations for each target year (e.g., five initial conditions each of 2036-2065 for 2050). It is population-weighted across the contiguous U.S.

The first row of Figure 4.2 shows alerts for sensitive groups (issued when $\text{AQI} > 100$). In the year 2000, these alerts are primarily driven by ozone, with the frequency of $\text{PM}_{2.5}$ -driven alert days increasing throughout the season and peaking around mid-August. The population-weighted chance of an “Unhealthy for Sensitive Groups” AQI peaks around 30% from approximately July 1st through mid-August. There is a clear rise in the probability of an alert at the start of the season and a decrease after the peak, though the chance of an “Unhealthy for Sensitive Groups” alert is higher at the end of the smog season than the beginning.

All counterfactuals increase the odds of an alert for sensitive groups. By 2100, the national average chance of an “Unhealthy for Sensitive Groups” alert reaches over 45% and remains at that level from late-June through late-August. This implies that, without emission reductions, vulnerable people could face nearly even odds of an alert, daily, throughout the smog season. Additionally, multi-pollutant risks rise, with more days in which both ozone and $\text{PM}_{2.5}$ trigger an alert (“Both” in Figure 4.2).

AQI alert chances for the general population grow by a proportionally larger amount than for the sensitive population. This is seen by comparing the alert probabilities in the bottom row of Figure 4.2 (“Unhealthy”) with those in the top row (“Unhealthy for Sensitive Groups”). At the start-of-century, these alerts were rare through May and only started increasing through June. The probability of an alert peaked at 10% around the start of August and decreased through September. Under the REF 2050 counterfactual, (Figure 4.2

(e)), ozone-driven “Unhealthy” alert days increase slightly, but there is a notable increase in PM_{2.5}-driven alerts, particularly around the middle of the smog season. This mid-century frequency is similar to REF 2000 at the start of the season; however, there is an increase in alert chance in September that is mostly due to an increase in higher risk “Both” ozone and PM_{2.5} alert days. In 2100 (Figure 4.2 (f)), the population weighted average chance of an “Unhealthy” AQI day peaks over 20%, which is slightly more than double the peak at the start-of-century period. The peak occurs about two weeks later in the year and lasts for a longer portion of the season than in REF 2000.

Climate change may double the alerts for sensitive groups across the smog season in 2100 compared to 2000 (Figure 4.3 (a)). In the REF 2000 concentrations, there are 20 “Unhealthy for Sensitive Groups” Air quality alerts caused by ozone, 4 by PM_{2.5}, and 2 by both pollutants concurrently each year. Under REF 2050 counterfactual concentrations, there are 40 “Unhealthy for Sensitive Groups” AQI days each year, with 11 from PM_{2.5}, 25 from ozone and 4 from both concurrently. The REF 2100 concentrations produce an average of 12 PM_{2.5} alert days, 34 ozone alert days, and 7 days with both pollutants generating alerts. This is a 200% increase in PM_{2.5} alert days, 70% increase in ozone alert days, and a 250% increase in dual alert days.

Climate policy that limits global warming to 2.5 °C or 2 °C reduces the number of alerts for sensitive groups (Figure 4.3 (a)). In 2050, both climate change mitigation policies reduce AQI alerts by 10%, from 40 to 36. In 2100, the 2.5C policy reduces AQI alerts by 30% compared to the REF concentrations, from 53 to 37. The 2C policy produces very similar outcomes, but it further reduces alert days to 36, which is 32% lower than REF. Both climate policies provide a 57% decrease in the extra harmful concurrent alert days

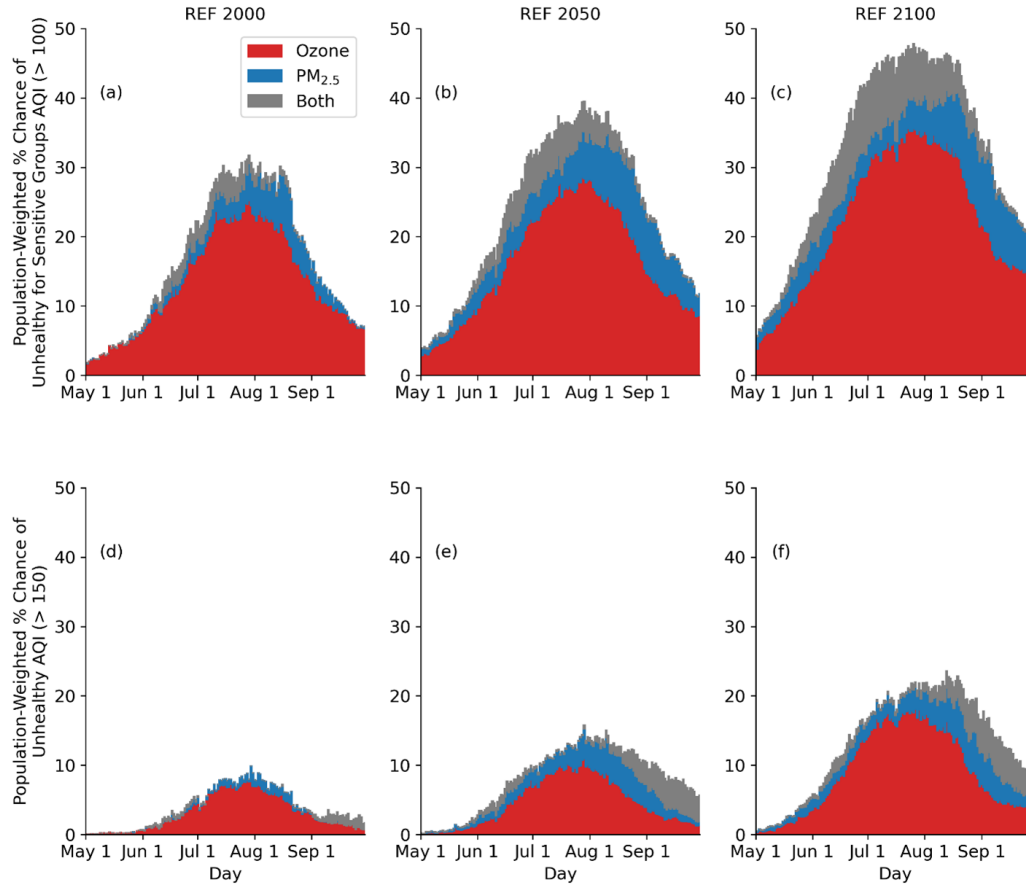


Figure 4.2: National population-weighted frequency of air quality alert days for different pollutants and threshold levels from May to September. Frequency is calculated as the proportion of time ozone, PM_{2.5}, or both pollutants exceed the defined threshold, over the contiguous U.S., and across 150 annual simulations for each target year (e.g., five initial conditions used to simulate each year of 2036-2065 for 2050). Upper row plots (a-c) correspond to AQI values reaching the “Unhealthy for Sensitive Groups” category, which is defined as AQI values > 100. Lower row plots (d-f) correspond to AQI values in the “Unhealthy” category (AQI values > 150). Plots show the distribution of AQI alerts over the smog season for counterfactual concentrations under REF 2000 (a,d), REF 2050 (b,e), and REF 2100 (c,f).

by end of century, lowering them from 7 in the reference case to 3 in each policy condition.

Figure 4.3 (a) shows a 38% increase in “Unhealthy for Sensitive Groups” AQI days by mid-century regardless of climate change mitigation policy. However, keeping warming to 2 °C or 2.5 °C limits increases in average “Unhealthy for Sensitive Groups” days between 2050 and 2100. In the 2.5C scenario, there is one additional AQI alert day between 2050 and 2100. The 2C scenario has the same number of alerts for sensitive groups in in the 2050 and 2100 concentrations.

The increase in “Unhealthy for Sensitive Groups” alerts is not uniform across the U.S. Some areas, such as the grid cells that encompass Chicago, St. Louis, and Indianapolis, see an additional two months per year of AQI in the “Unhealthy for Sensitive Groups” category (Figure 4.3 (b)). Increases in AQI alert days are most severe in the eastern half of the U.S., particularly the northeast. With REF 2100 concentrations, Los Angeles is the location with the highest overall number of days with AQI > 100 in smog season. In that grid cell, the AQI is in the “Unhealthy for Sensitive Groups” category for 81% of the smog season, which is 124 days per year.

The areas that see the largest decrease in AQI days due to climate policy are the same areas that see the greatest increases from unmitigated climate change. The areas containing Chicago, St. Louis, and Indianapolis would see 37 fewer AQI alert days annually with the 2C concentrations than they would under REF. (Figure 4.3 (c)). While these benefits follow the same spatial pattern as the harms in Figure 4.3 (b), the magnitudes are lower – reinforcing that the climate penalty degrades air quality under all policies.

While ozone drives air quality alerts (Figure 4.3 (a)), PM_{2.5} drives the changing eco-

conomic burden (Figure 4.3 (d)). Figure 4.3 (d) shows the additional health-related economic burden from air pollution under each counterfactual concentration compared to the start of century. The portions of the burden attributed to ozone and $\text{PM}_{2.5}$ are shown separately. While ozone alerts comprise 52% of additional alerts for the REF 2100 counterfactual concentration (Figure 4.3 (a)), it only accounts for 6% of additional economic burden (Figure 4.3 (d)).

Increasing alert days explain most of the changing economic burden. In 2050, the 2.5C and 2C counterfactuals have 14 additional “Unhealthy for Sensitive Groups” AQI alert days compared to 2000 (Figure 4.3 (a)). Similarly, in 2100, the 2.5C and 2C counterfactual concentrations have 14 and 15 additional “Unhealthy for Sensitive Groups” AQI alert days compared to 2000 (Figure 4.3 (a)). However, in both 2050 and 2100, the valued health burden of the 2.5C policy case is higher than the 2C scenario. 2.5C has a 14% higher health burden in 2050 and is 80% higher in 2100. Again, $\text{PM}_{2.5}$ drives almost all these additional health impacts.

Avoidance adaptation reduces morbidity and mortality. Figure 4.4 shows the mean health-related economic benefit of avoidance adaptation based on 5000 Monte Carlo simulations representing uncertainty in health outcomes and economic valuation (95% confidence interval in Table B.5). Specifically, it shows the value of the reduced risk of morbidity and mortality achieved by reducing exposure through remaining indoors during air quality alerts, calculated using Equation 8. It assumes that full population experiencing an alert for “Unhealthy” air complies and reduces their outdoor time to zero (converting it to time in residences). Full compliance is much higher than observed [97], thus this assumption provides an upper bound on the benefits achieved by adaptation.

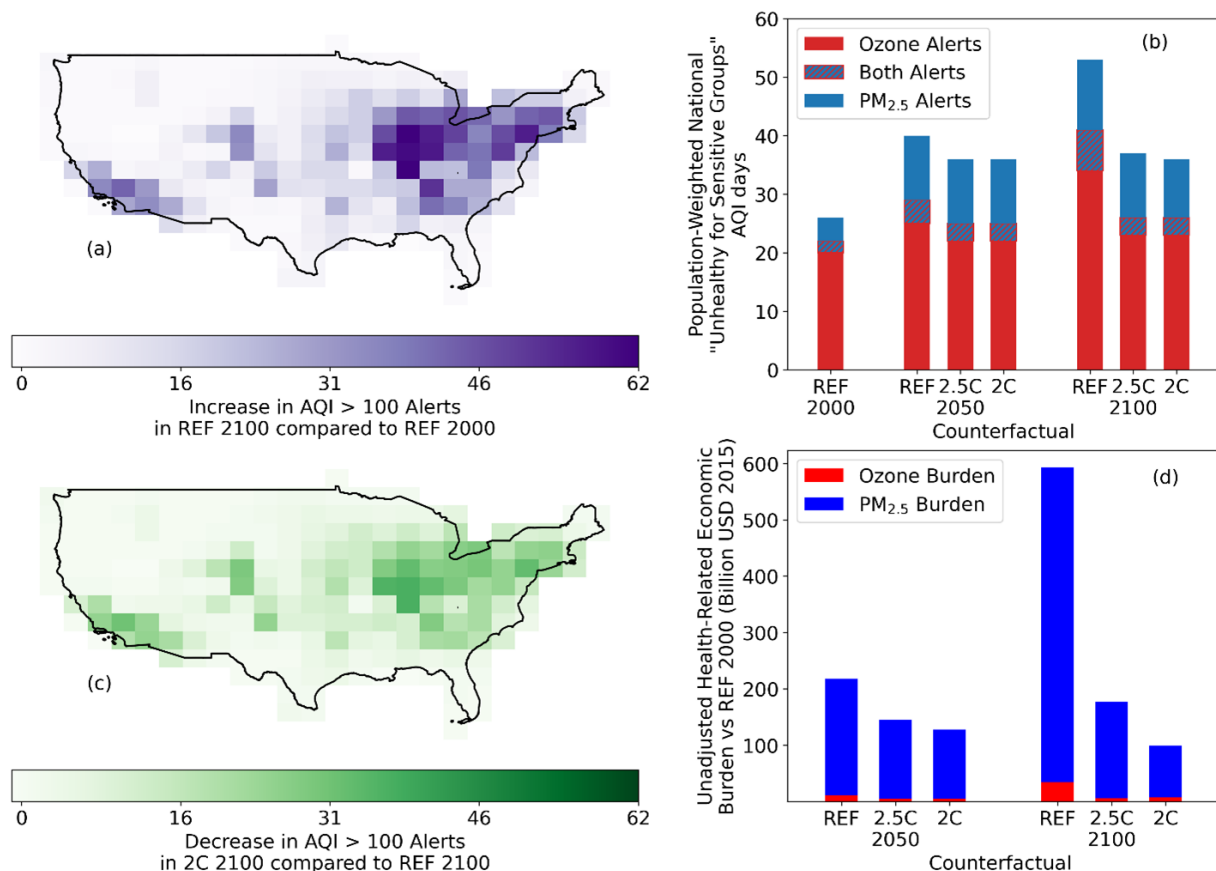


Figure 4.3: Air quality alerts for sensitive groups (i.e., air deemed “Unhealthy for Sensitive Groups”, with AQI > 100) under future concentrations and future health burden for full population. (a) Increases in alerts in 2100 concentrations compared to 2000 concentrations in the absence of climate policy. (b) National population-weighted number of alerts during the smog season (c) Decreases in alerts with end-of-century concentrations for the 2C climate policy compared to no policy. (d) Bar charts showing the health-related economic burden for counterfactual concentrations relative to the start-of-century period (in billions of 2015 USD). Health effects are broken down by responsible pollutant (ozone or PM_{2.5}). Results are based on projected concentrations only, and are not adjusted for population or economic growth.

When people adapt, they reduce their risk of morbidity primarily by reducing their exposure to ozone (Figure 4.4 (a) and (b)). This is expected when populations adapt

to ozone-driven alerts (Figure 4.4 (a)), but it also remains true for adaptation to PM_{2.5}-driven alerts (Figure 4.4 (b)). This is partially because moving inside is typically more effective at reducing exposure to outdoor ozone (a 30% reduction) than outdoor PM_{2.5} (a 6% reduction). There are also more ozone-driven alert days than PM_{2.5}-driven days.

Adapting to all ozone-driven alerts and all PM_{2.5} -driven alerts avoid a similar amount of premature mortality (Figure 4.4 (c)-(d)). We find that climate policy reduces the number of alerts, thereby reducing the potential gains from adapting. Specifically, full compliance with alerts would yield around \$15 Billion (in 2015 USD) in each year under climate policy, compared to \$20 Billion in 2050 and up to \$45 Billion in 2100 under the reference case (REF). When adapting to ozone, the mortality-related adaptation benefits are evenly split between reductions in ozone and PM_{2.5} exposure, respectively (Figure 4.4 (c)). When adapting to a PM_{2.5}-driven alert, however, benefits are dominated (over 80%) by reductions in PM_{2.5} exposure.

Even full compliance with alerts for “Unhealthy” air cannot completely offset rising climate-related risks from the start of century. Avoidance adaptation to both PM_{2.5} and ozone can offset between 15% of the burden from rising alerts (under reference concentrations), and 40% (with 2C 2100 concentrations), of the increased health burden due to the climate penalty (Figure 4.4).

Most of the air pollution-related health burden falls on seniors. Figure 4.5 (a) shows the average proportion of the mortality burden that each population group experiences across all counterfactual concentrations. Seniors make up 65.4% of the mortality burden from air pollution even though they are 12% of the total population (Figure 4.5 (a)). Next, the

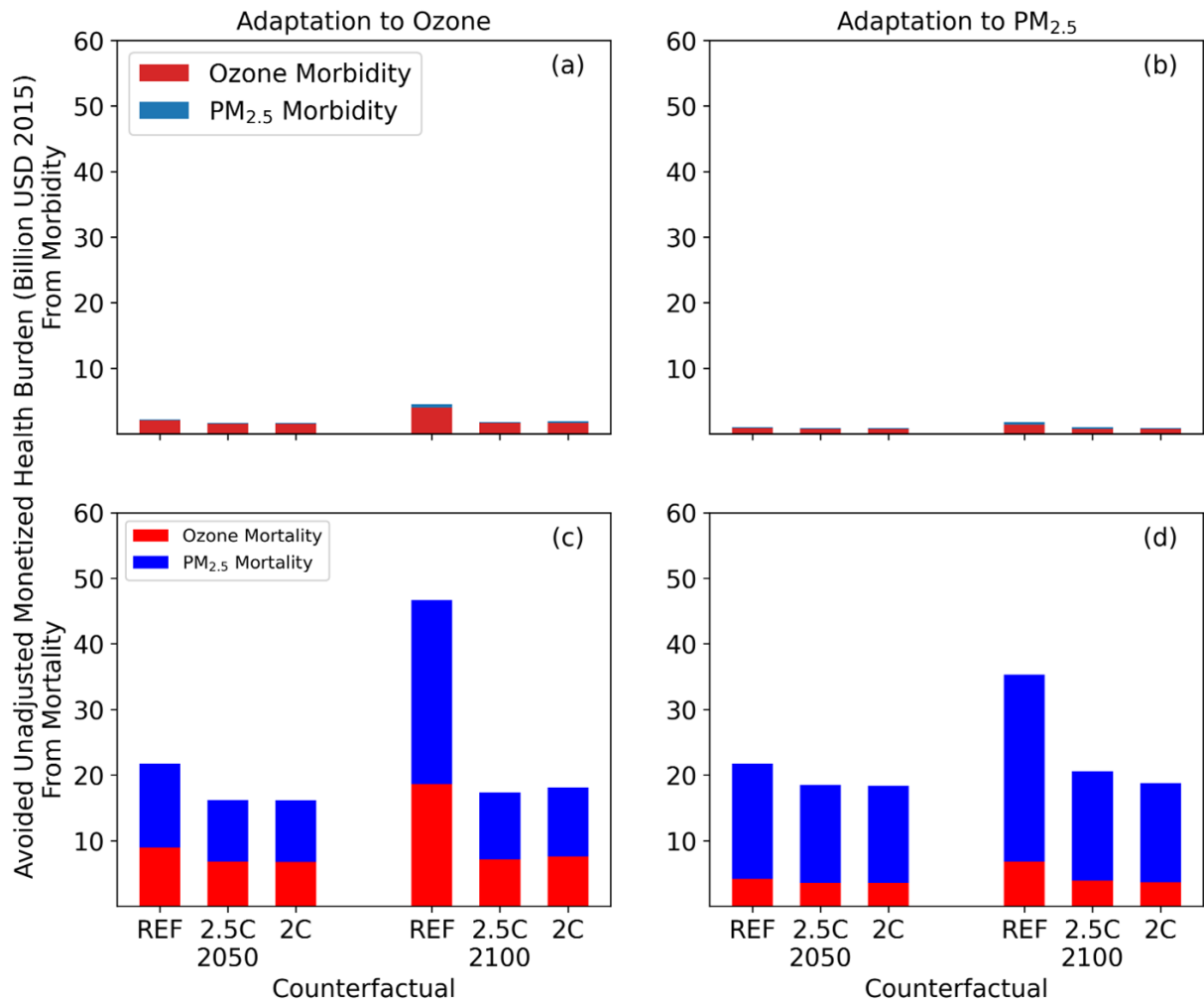


Figure 4.4: Health benefits of avoidance adaptation under different counterfactual concentrations (billions of 2015 USD). The avoided health burden, or health benefit, is gained by switching outdoor time to residential time during air quality alerts that apply to the full population (AQI > 150, “Unhealthy”). Benefits are shown by the contribution of reducing exposure to ozone (red) and PM_{2.5} (blue), respectively. Adaptation to alerts triggered by high ozone levels is shown in (a) and (c). Adaptation to PM_{2.5}-driven alerts is shown in (b) and (d). Adaptation benefits from avoided morbidity are shown in (a) and (b) and adaptation benefits from avoided mortality are shown in (c) and (d).

36-64 age range makes up 29.1% of the air pollution health burden and represents 39% of the population. The final two age brackets, 18-35 and Under 18, only make up a combined 5.6% of the health burden from air pollution.

Adaptation health benefits differ greatly between age groups. Figure 4.5 (b) shows the health-related economic benefits that each age group gets from avoidance adaptation. Benefits are based on the average concentrations across counterfactual scenarios to reflect mean differences between age groups across all scenarios examined. The 95% confidence interval shown comes from uncertainty in health responses and their valuation. Adaptation benefits for the senior population are significantly higher than any other age group (Figure 4.5 (b)). Seniors receive a health-related economic benefit of \$80 (95CI: \$5, \$161) and \$74 (\$3, \$102) for each $\text{PM}_{2.5}$ and ozone adaptation day, respectively. This is 14 times higher than the next closest age range (36-64) and up to 75 times higher than the benefits received from the 18-35 age group.

The AQI thresholds for “Unhealthy for Sensitive Groups” and “Unhealthy” do not match the difference in risk between sensitive and non-sensitive groups. The difference in health risk comes from the difference in the baseline incidence rate of different health outcomes (Y_0 in Equation 4.2). Based on that, the Over 65 population has a 30 times higher risk of premature mortality than the 18-35 group. However, the ratio of concentrations between AQI thresholds for sensitive groups and the general population is 1.56 for $\text{PM}_{2.5}$ and 1.21 for ozone.

Further, a cost-benefit perspective provides different AQI thresholds for adaptation, especially for seniors. Seniors are outside for 43 minutes per day, on average. Previous

work estimating the costs of adapting by staying inside provides a mean of \$32/hr (range of \$10.15-\$75.65/hr) [162]. These hourly costs are lower than the hourly health-related benefits of \$112 (95CI: \$7, \$225) and \$103 (\$4, \$142) for adapting when PM_{2.5} and ozone are at their “Unhealthy” AQI thresholds, respectively. To have positive net benefits from adapting, the average senior would adapt at AQI value of 71 for PM_{2.5} based on premature mortality benefits. Accounting for morbidity and ozone-related benefits would decrease the AQI value at which they could adapt to reap net benefits.

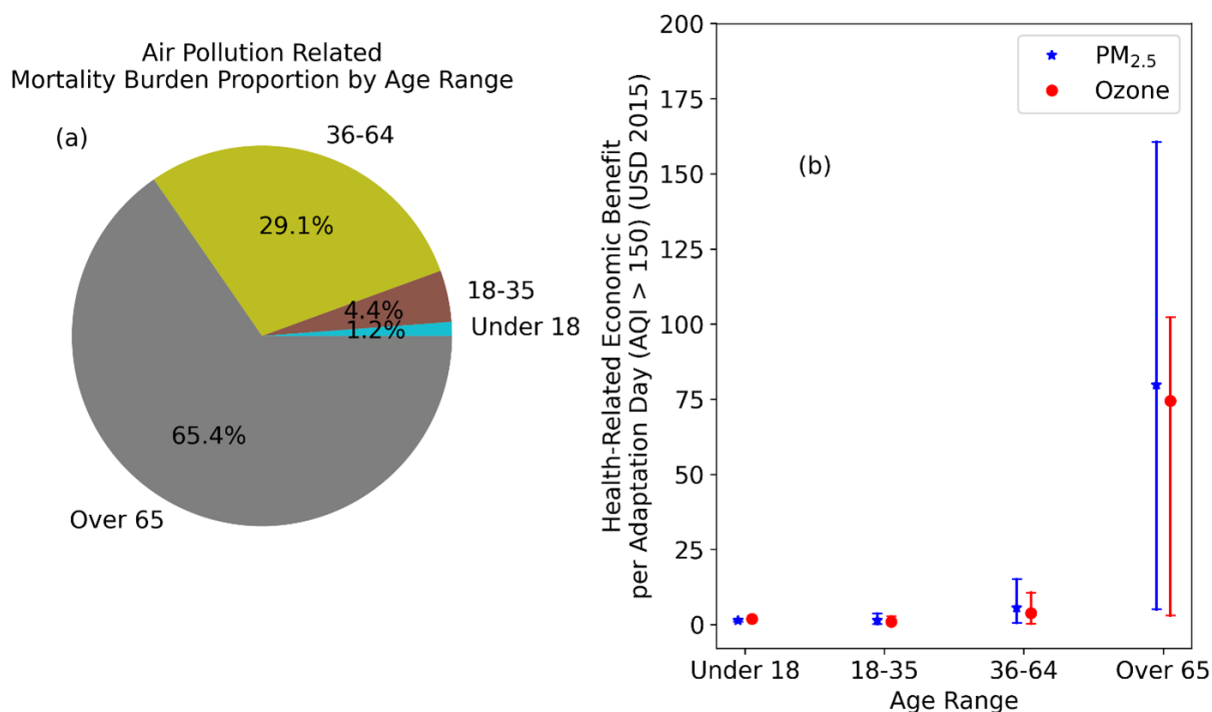


Figure 4.5: Total air pollution related health burden by age (based on the average concentrations across all scenarios examined). (a) Proportion by age group (b) Health benefit per day adapting to an air quality alert for the general population. Shown for alerts triggered by PM_{2.5} (blue) and ozone (red) for each age range, including the mean and 95% confidence interval for uncertainty related to health responses and their valuation.

4.6 Discussion

4.6.1 Changes in Future Air Quality Alerts

Our results show conditions for air quality alerts will become more common and widespread in the absence of mitigation policy, leading to 33% of the population having air quality considered “Unhealthy for Sensitive Groups” ($\text{AQI} > 100$) during smog season by end-of-century (Figure 4.1). This is 9 times as many people as the start of this century. As the mean AQI increases, the chance of alerts grows for sensitive groups (Figure 4.2 (a-c)) and the general population (Figure 4.2 (d-f)). On average across the U.S., we find longer periods of high air pollution affecting more people. In some areas, there could be up to two additional months of “Unhealthy for Sensitive Groups” alerts per year (Figure 4.3 (b)). We find that accounting for ozone changes leads to larger total increases in air quality alerts (up to 62 additional days per year vs 50), however, the relative impact is smaller than in previous work that only considered $\text{PM}_{2.5}$ (2 times as many alerts vs 4 times) [162].

The increasing number of alert days might make alerts less effective due to adaptation fatigue. Previous studies on air quality alert compliance found that compliance drops drastically subsequent alert days [92, 93]. Thus, it seems unlikely then, that populations in the counterfactual concentrations presented in this study would adapt for the national average 53 days per year under REF 2100 and especially not the 124 days in Los Angeles. Our estimates of full compliance adaptation (Figure 4.4) are likely overestimates adaptation benefits, highlighting the need for climate change mitigation.

4.6.2 Limitations of the AQI to Promote Adaptation

Because of its focus on short-term concentrations [86], alert thresholds do not correspond well with risks of pollution-related morbidity and mortality that are driven by changes in long-term average exposures. Responding to alerts suggesting the air is “Unhealthy” or “Unhealthy for Sensitive Groups” yields health-related benefits (Figure 4.4). Although adaptation is a short-term action that reduces exposure on a single day, most of the benefit comes from avoiding premature mortality through reducing average chronic average exposure.

While there are benefits to a single-pollutant index like the AQI, it masks the benefits of adapting when multiple pollutants are elevated. Thus, multi-pollutant indices, like Canada’s Air Quality Health Index, might offer advantages, especially as days when both ozone and $\text{PM}_{2.5}$ reach hazardous levels grow. Our findings show that much of the benefit of adapting to ozone is gained through reducing $\text{PM}_{2.5}$ and vice-versa (Figure 4.4). Accounting for more than one pollutant increases the estimated benefits of responding to air quality alerts substantially.

A binary, threshold-based approach to air quality alerts may obscure increases in risk. Population-weighted average number of “Unhealthy for Sensitive Groups” air quality alert days was the same for concentrations derived from the 2.5C and 2C policy cases in 2050 and almost the same in 2100 (Figure 4.2). However, the health burden of those pollutant levels was very different, with 2.5C having a 14% higher burden in 2050 and 80% higher in 2100 (Figure 4.3). However, the increase in risk would not be communicated to the public through AQI alerts because there were the same number of days above the “Unhealthy”

AQI threshold (Figure 4.3). Thus, considering alert days alone isn't enough to distinguish health-related economic impacts when comparing the effects of policy.

4.6.3 Implications for Sensitive Groups

Our age-specific results suggest that air quality information could be better tailored to elderly population, including in terms of threshold levels, communication channels, and guidance. Firstly, AQI level to trigger communication to seniors could be lowered.

Over 65 populations have 14 times higher adaptation benefits than any other age group. On average, their benefits exceed their costs of adapting at an AQI threshold of 71 (for PM_{2.5}-driven alerts). This AQI threshold will drop when both pollutants are present. Our results show that, without emission reductions, days when both pollutants exceed the NAAQs will likely increase, further strengthening the need to reconsider the level and content of communication. Communication channels will also continue to change. Currently, prioritizing seniors may involve focusing on television, newspapers, and medical practitioners [16, 112]. The advice provided through those channels should also reflect their conditions. While some seniors spend a good deal of time outside, approximately 47% are housebound. We suggest that adaptation guidance for seniors include exposure reduction through two pathways. First, seniors who do not spend time outside should be advised to reduce pollution levels in their indoor environment. This includes improved filtration [108, 104], using portable air cleaners [184, 185], and keeping windows closed during high outdoor pollution events (with consideration for potential heat exposure) [162]. Seniors who do spend time outside should consider staying indoors and shifting activity intensity

to places and times with lower pollution during high pollution episodes. Well-fitting, high efficiency face masks can reduce pollution exposure [186] both indoors and outdoors and can be advised as tolerated.

4.6.4 Comparison with Other Studies

The most direct approach to protect health from outdoor air pollution is to reduce emissions of air pollutants. However, the climate penalty can degrade these efforts [7]. One strategy to mitigate the climate penalty is to implement climate policy. Limiting warming to 2.5 °C and 2 °C at end-of-century reduces the climate penalty health burden by 33% and 41% under 2050 concentrations and 70% and 83% with 2100 concentrations respectively. This aligns well with a previous study (Saari et al., 2019) which found that climate policy could reduce the climate penalty health burden by up to 50% in 2050 and up to 88% in 2100 [7]. Our findings are slightly lower because we did not project to future populations or economies, we used updated concentration-response functions and recently published de-biased ozone concentrations with improved performance for ozone extremes [161].

Our quantified adaptation effectiveness is different from values used in previous studies. Our avoidance adaptation PM_{2.5} exposure reduction of 6% for remaining indoors is significantly lower than the 35% used by Brook et al. (2024) [99]. Our ozone and PM_{2.5} reduction values are also significantly higher than those used in Buonocore et al. (2021). This partially explains why we found higher benefits per adaptation than they did (up to \$14/hr) [17]. Other explanations include different concentration data, population data, and health impact functions. Our estimates represent a contribution to this literature be-

cause they are the first to use detailed time-use and housing data to describe exposure for multiple pollutants across different microenvironments.

4.6.5 Limitations and Future Work

While our study provides valuable insight into air quality alerts and adaptation, it has several limitations. We chose to use counterfactual concentrations to isolate the effect of air pollution changes in future climate conditions on a static, current population. However, this meant not projecting future populations or economies. Larger, older populations and larger, wealthier economies in the future would both cause the health-related economic burden of air pollution to be up to 6 times higher than presently reported (Figure B.4). Also, to produce many future annual simulations, our study uses relatively coarse grid cells (2° by 2.5°). This can lead to spatial smoothing or averaging of air pollution values and may hinder capturing extreme AQI values. It is likely that using a finer grid cell would result in higher pollution values and more frequent alerts in some places, and less frequent alerts in others. While previous evaluations of our concentrations found that they aligned well with both measured air quality and projected estimates of the climate penalty [162, 121], using a large, multi-model ensemble would aid in reducing the effects of variability and model uncertainty. As with all health impact study work, we chose health impact functions to relate changes in concentration to changes in health impacts. Study selection, concentration-response function shape, pooling, and use of threshold concentrations are some of the factors that could yield different health outcomes. Age-related analysis could be improved by including age-specific baseline risks (for those not age-stratified in

BenMAP), health impact functions reflecting effect modification by age, and age-varying risk preferences and costs of illness.

Future studies should quantify the benefits of different types of adaptation. AQI focuses on short-term risk reduction based on the concentration of a single pollutant. AQI-recommended adaptation such as reducing outdoor activity intensity benefits can and should be calculated. However, it is also important to study other strategies, like improving building airtightness, using portable air cleaners, and improving building HVAC filtration, that reduce chronic exposure to air pollution of outdoor origin. Future work could also explore alternative metrics, including one designed to address chronic exposure. Further, approaches for more individualized guidance should be explored, including those that consider individual risks, adaptation capacity, and preferences.

4.7 Conclusion

Air quality alerts are used as a means of protecting human health when pollution levels are high. Under climate change, we find a potential increase in days with high ozone and $\text{PM}_{2.5}$. A growing elderly population shows the largest gains from adapting to such polluted days, even at much lower thresholds than currently suggested. We find, however, that the current single-pollutant alert thresholds can mask the benefits of adapting to pollutant mixtures, as well as the variation of benefits among individuals.

We found that, without emission reductions, climate change may lead to a tripling of air quality alerts for the general population, and a doubling for the sensitive population by 2100 compared to 2000. Climate policy can significantly reduce the number of alerts

per season and the adverse health impacts caused by the pollutants. Most of the future alerts are caused by high ozone concentrations during the summer smog season. However, most of the benefits of adapting are due to reducing $\text{PM}_{2.5}$ exposure. The single pollutant reporting system used by the AQI does not currently consider these benefits of multiple exposure reduction.

Our findings suggest that, from a cost-benefit perspective, current air quality alerts may over-provide risk protection for the healthy, younger population while under-providing it for sensitive groups, especially the elderly. When adapting to ozone, the benefits for higher-risk populations were 75 times higher than the benefits for lower risk populations. At the same time, the threshold for “Unhealthy” AQI from ozone was only 1.21 times higher than the threshold for sensitive groups. For $\text{PM}_{2.5}$, higher-risk populations received 59 times more benefit than lower risk groups, yet the ratio of alert thresholds was 1.56 between these populations. More personalized adaptation guidance, calculated and delivered on an individual level, could promote more effective adaptation.

The effectiveness of air quality alerts relies on individual awareness and compliance. Other strategies could improve adaptive capacity that are more robust to such behavioral factors, including adaptation fatigue. Such strategies include improving residential building airtightness, filtration, and use of portable air cleaning devices.

Chapter 5

Population Exposure to Outdoor Particulate Matter: Role of Buildings, Behavior, Ambient Air Quality, and the COVID-19 Pandemic

The work in this chapter has been submitted for publication.

5.1 Abstract

Reducing exposure to outdoor fine particulate matter ($\text{PM}_{2.5}$) can protect health and extend lives. The COVID-19 pandemic considerably changed $\text{PM}_{2.5}$ exposure by altering time use, mask-wearing, and outdoor air quality. We investigate this change for individuals in the 25 most populous U.S. cities before and during the pandemic by matching activity, location, and local concentration data. We find that average exposure to $\text{PM}_{2.5}$ of outdoor origin likely increased by 5% during the pandemic for non-maskers. This increase occurred

even as outdoor concentrations decreased by 4% on average. Exposure increases were higher for those in high-income, professional occupations, and for people living in leaky homes. Wearing masks in public indoor spaces also provided protection from $\text{PM}_{2.5}$. Most (66%) exposure to ambient $\text{PM}_{2.5}$ occurs within residential environments, and the pandemic increased this (to >75%). Reducing the infiltration of outdoor $\text{PM}_{2.5}$ in residences can provide similar protection to masking, and boosts the protection achieved by complying with air quality alerts. The largest exposure reductions are earned by improving outdoor air quality; however, behavioral differences can offset ambient improvements and should be considered when evaluating interventions designed to reduce exposure.

5.2 Introduction

Exposure to fine particulate matter ($\text{PM}_{2.5}$) of outdoor origin is harmful to human health and a top ten risk factor for premature death worldwide [11, 187, 188]. Factors affecting this exposure – including time use, masking, and outdoor air quality – changed during the recent COVID-19 pandemic. Here, we estimate the resulting change in exposure to outdoor $\text{PM}_{2.5}$. We evaluate the role of underlying factors affecting exposure to draw lessons on the efficacy of interventions – enshrined in current standards and guidelines – to protect human health.

$\text{PM}_{2.5}$ is particulate matter with an aerodynamic diameter less than or equal to 2.5 μm . It can harm human health by entering the body via inhalation, ingestion, and dermal contact. The amount of $\text{PM}_{2.5}$ inhaled depends on the level of airborne particles, breathing rate and pattern [189, 190], and the presence of any barriers to prevent particle inhalation,

such as an N95 mask [191]. Each of these factors can be leveraged to reduce inhalation of harmful particles [164].

The first factor determining exposure is the amount of $\text{PM}_{2.5}$ in the air, typically expressed as mass concentration. While $\text{PM}_{2.5}$ can be generated indoors or outdoors, here, we focus on $\text{PM}_{2.5}$ of outdoor origin. Outdoor concentrations of $\text{PM}_{2.5}$ have generally decreased in recent decades across the United States due to emission reductions [192], particularly in urban areas [193]. These improvements have reduced racial and ethnic disparities in $\text{PM}_{2.5}$ exposure [61, 194]. However, disparities and health risks remain, with 36% of reporting counties exceeding the National Ambient Air Quality Standard of $9 \mu\text{g}/\text{m}^3$ [195, 32]. Ninety-one percent of reporting counties have outdoor concentrations exceeding safe levels set by the World Health Organization of $5 \mu\text{g}/\text{m}^3$ [195, 196].

Polluted outdoor air can enter the indoor environment. This occurs through infiltration (e.g., cracks and leaks), natural ventilation (e.g., open windows), or mechanical ventilation (e.g., building HVAC systems) [197]. The fraction of outdoor $\text{PM}_{2.5}$ that remains airborne indoors is called the infiltration factor, or F_{INF} [198]. Measured F_{INF} varies across microenvironments (e.g., residences, commercial buildings, and vehicles), thereby affecting individual exposures [199].

Studies accounting for F_{INF} suggest that most exposure to $\text{PM}_{2.5}$ of outdoor origin happens indoors [198] – particularly at home, where people spend most of their time [100]. In fact, $\text{PM}_{2.5}$ entering homes from outdoors is the greatest contributor to premature death associated with exposure to this pollutant [144]. Reducing this exposure by lowering F_{INF} can involve two strategies: preventing $\text{PM}_{2.5}$ from entering buildings and removing $\text{PM}_{2.5}$

that enters. Making building envelopes more airtight reduces leakage and thus reduces particle infiltration [106, 200]. $\text{PM}_{2.5}$ that infiltrates can be removed via filtration or air cleaning. In mechanical ventilation systems commonly used in commercial buildings, increasing filtration efficiency can reduce indoor concentrations of $\text{PM}_{2.5}$ by over 30% [201]. In residential buildings where recirculating HVAC systems are commonly used, upgrading to filters with higher efficiencies reduces the fraction of outdoor $\text{PM}_{2.5}$ that remains airborne indoors [102]. Portable air cleaners with high-efficiency filters can also help remove particles from indoor air through enhanced localized filtration [202, 184].

Our activities affect the amount of $\text{PM}_{2.5}$ inhaled. Activities that require exertion, like exercise or physical labor, require faster breathing rates that inhale more air. The level of exertion is measured by the Metabolic Equivalent of Task (MET), with an MET of one reflecting the oxygen used by a reference individual sitting quietly [203]. People can protect themselves by wearing masks to filter particles from the air before they are inhaled. The fraction of $\text{PM}_{2.5}$ that still gets through a mask is called the Total Inward Leakage (TIL), which varies with mask material and fit [204].

Current guidance aims to protect the public from acute exposure to outdoor $\text{PM}_{2.5}$ by encouraging behavior changes. In the United States, alerts about unhealthy air are issued based on the Air Quality Index (AQI) [6]. During alerts, people are encouraged to reduce or limit physical exertion and time outdoors [6, 205]. For wildfire smoke, specifically, they are guided to use masks (specifically, N95 or P100 respirators) when outdoors, and keep indoor air clean [6, 205]. Empirical studies have linked alerts to behavioral change [92, 93, 206, 207] and improved health outcomes [94, 95]. However, their effectiveness is limited by public awareness and capacity to adapt [162]. Previous work shows that only a

small fraction of Americans adapt to poor air quality [5], and some cannot access protection afforded by clean indoor environments [162].

The COVID-19 pandemic disrupted factors influencing exposure to outdoor PM_{2.5}. Most (though not all [208]) studies of the early pandemic found a 3-21% decrease in outdoor PM_{2.5} [209, 210, 211, 212, 213]. This drop in PM_{2.5} outlasted the lockdowns, with a national population-weighted mean decrease of 3-4% from April 2020 to March 2021 [213]. These reductions were caused primarily by shifts in where and how people spent their time (i.e., time-activity patterns). Throughout the pandemic, many Americans spent more time at home instead of commuting to work or leaving home to shop, socialize, or dine. Overall, the share of Americans working from home increased twelvefold (from 5% to between 35% and 62%), with a 30% drop in travel [214, 215]. This shift varied by occupation and family responsibilities, with implications for COVID-19 exposure risks [216, 217, 218]. Following public health guidance, most Americans reported wearing masks indoors when leaving home [219], particularly in commercial or institutional settings [220].

Pandemic restrictions also affected physical activity, including reducing outdoor recreation among certain populations [215, 221, 222]. While people were spending more time indoors, the pandemic also drew attention to indoor particulate matter – specifically, virus-laden particles capable of transmitting the disease [223]. Measures to reduce the risks of airborne transmission of COVID-19, like increasing ventilation, filtration, and supplemental air cleaning also affect total exposure to airborne particles, including those originating outdoors [224].

The COVID-19 public health emergency thus offers important lessons for reducing

health risks from air pollution. Interventions such as reducing outdoor concentrations, mask wearing, and shifting activities all reduced exposure to particulate matter of outdoor origin. During the pandemic, behavioral levers, such as staying home and masking, saw much higher uptake than typical compliance during air quality alerts, thus providing a real-world test of their effectiveness and their limitations.

Previous studies estimated a drop in premature mortality attributable to outdoor particulate matter in the U.S. during the pandemic (ranging from less than 1% to 12% [209, 211, 213]). These estimates relied on changes in outdoor concentrations to represent the shift in exposure. This is consistent with health impact assessment literature and aligns with how the exposure-response relationships were developed [154]. However, if more people were wearing masks, spending time outdoors, or living in leaky houses, these behavioral and environmental factors could have further influenced exposures in ways not yet captured in the literature.

Here, we examine factors that contribute to exposure to $\text{PM}_{2.5}$ of outdoor origin across the U.S. from 2008-2020. We estimate exposure in the top 25 most populous Core-Based Statistical Areas (CBSA) using outdoor concentrations, time-activity patterns, masking, and infiltration across four microenvironments (Residential, Commercial, Vehicle, and Outdoors). We use the COVID-19 pandemic as a case study to explore the value of current guidance and standards in $\text{PM}_{2.5}$ exposure reduction. Specifically, we compare the impact of recommended actions associated with air quality alerts (moving indoors), wildfire smoke (masking outdoors), outdoor air quality standards (the U.S. National Ambient Air Quality Standard and World Health Organization Guideline for $\text{PM}_{2.5}$), and improving residential building airtightness. The case of the COVID-19 pandemic allows us to explore the effect

of competing factors on exposure, test the limits of current guidance and standards, and inform future interventions for protecting public health.

5.3 Methods

We estimate the effect of different factors on exposure to PM_{2.5} of outdoor origin. These factors include outdoor PM_{2.5} concentrations, particle infiltration (F_{INF}), time-activity patterns, and masking. We estimate average daily personal exposures in the U.S. from 2008 through 2020, comparing the pre-pandemic and pandemic periods. We then test the effects of perfect compliance with guidelines and standards associated with adaptation behavior, environmental quality, and buildings on reducing average exposure. This section details our data sources, equations, and policy interventions.

5.3.1 Average Daily Exposure

We calculate daily personal exposure ($E_{d,i}$) for each individual i and day, d , using Equation [5.1](#)

$$E_{d,i} = C_{d,c} \times R_{d,i} \quad (5.1)$$

$C_{d,c}$, is daily mean outdoor PM_{2.5} mass concentration ($\mu\text{g}/\text{m}^3$) in Core-Based Statistical Area (CBSA) c . $R_{d,i}$ is the exposure ratio, or the ratio of personal average PM_{2.5} concentration of outdoor origin to outdoor PM_{2.5} concentration. $R_{d,i}$ adjusts the outdoor

concentration to reflect exposure to PM_{2.5} of outdoor origin throughout the day with ratios representing infiltration, activity intensity, and masking, respectively, over the 1440 minutes of the day, via Equation 5.2.

$$R_{d,i} = \sum_{t=1}^{1440} F_{INFt,i} \times I_{t,i} \times M_{t,s,i} \quad (5.2)$$

$F_{INFt,i}$ is the infiltration factor of the environment at minute t . $I_{t,i}$ reflects the different breathing rates of activities using the ratio of the MET of the activity at time t to daily mean effective MET (weighted by the time spent at each MET value). $M_{t,s,i}$ is the Total Inward Leakage (TIL) for the style of mask worn s (for $s = \text{none}$: 1 surgical-type: 0.25, or N95-type: 0.05) [191, 204].

5.3.2 Study Population

We determined our study population based on available collocated data for outdoor concentrations and time use. Our source for time-activity data was the American Time Use Survey (ATUS) [170]. ATUS has been published annually by the U.S. Bureau of Labor Statistics (US BLS) since 2003. ATUS respondents are a subset of the US BLS's Current Population Survey (CPS). Data are collected via telephone interviews. The ATUS/CPS survey results used in this study include activity description, timing, resident occupation, and location codes (see Tables C.1-C.4).

ATUS is a nationally representative survey. Though our study population of the top 25 most populous CBSA represents approximately 50% of the total United States population

[225], we use ATUS weights when aggregating results across respondents to improve the out-of-sample generalizability of our findings. We used Equation 5.3 to find mean daily exposure across the study population, E_d .

$$E_d = \frac{\sum_i w_i E_{d,i}}{\sum_i w_i} \quad (5.3)$$

Where w_i is the final weight for respondent i published by ATUS [170].

5.3.3 Outdoor Pollution Concentration

We use outdoor $\text{PM}_{2.5}$ concentrations from the U.S. Environmental Protection Agency (EPA) Air Quality System (AQS) [74]. We apply daily mean ground-based monitor $\text{PM}_{2.5}$ measured with EPA Federal Reference Methods and Federal Equivalent Methods from the years 2008 – 2022 [75], to capture our pre-pandemic period as well as all studied para-pandemic periods.

To estimate exposure, we use outdoor $\text{PM}_{2.5}$ pollution levels for each respondent’s CBSA on the day of their recorded activities. We matched monitor data with the date, time, and CBSA values in ATUS. For CBSAs with more than one monitor reporting, concentrations were averaged. Through this matching, we included 27,346 respondents from the top 25 most populous CBSAs (Table C.5). The details on the corresponding F_{INF} estimation and activity classification are provided below.

5.3.4 Microenvironment Infiltration Values

We consider four microenvironments: residential buildings (Residential); non-residential buildings (Commercial); on-road vehicles (Vehicles), and Outdoors. Each microenvironment provides a different level of protection against pollutant infiltration, characterized by the infiltration factor (F_{INF}), summarized in Table 5.1.

Table 5.1: F_{INF} by microenvironment.

Microenvironment	Representative F_{INF} Value	Source
Residential	Values for each CBSA found in Table C.5.	Calculated using Equation 4 with National Renewable Energy Laboratory (NREL) Res-Stock [178] ACH values.
Commercial	0.35	Lower range of 0.35 and 0.49 used in Fisk and Chan (2017) [108] and Azimi and Stephens (2020) [144], respectively.
Vehicle	0.6	Fisk and Chan (2017) [108], based on Rodes et al. (1998) [226] and similar to 0.61 for outdoor ventilation mode driving in Hudda and Fruin (2013) [181].
Outdoors	1	

We calculated F_{INF} for the Residential microenvironment for each CBSA (c) with Equation 5.4.

$$F_{INF_c} = \frac{P \times ACH_c}{ACH_c + \beta} \quad (5.4)$$

P , the penetration factor, was 0.73 based on the findings of Zhao and Stephens [179].

ACH_c is the number of air changes per hour under natural conditions for a typical residential building in CBSA c . To find ACH_c , we gathered ACH_{50} values, representing air changes per hour under a 50 Pa pressure difference, from the National Renewable Energy Laboratory (NREL) ResStock [178]. ResStock reported ACH_{50} values for over 150,000 buildings representing the U.S. housing stock. We used mean ACH_{50} values of all buildings in the same ASHRAE climate zone as CBSA c to estimate ACH_{50c} . We divided ACH_{50c} by 16 to calculate ACH_c following Chan et al. (2005) [227]. β is the deposition rate per hour of indoor $PM_{2.5}$ particles. We used a β value of 0.44 based on Persily et al. (2010) [124].

5.3.5 Time Use by Microenvironment

ATUS respondents report their activities over the previous day in minutes. We assigned each activity to a microenvironment based on its ATUS activity code to find $F_{INF,t,i}$. We adapt Hoehne et al. (2018)’s approach to classify each activity as occurring Indoors, Outdoors, or, if the activity description is ambiguous, Unknown [130] (see Table C.5). We assign Unknown activities – usually occurring at home – as indoors, following Hoehne et al. (2018). We classify F_{INF} for the respondent’s place of work based on their occupation code (Table C.2).

5.3.6 Activity Intensity

Greater intensity reflects a higher breathing rate and thus a larger inhaled dose. We therefore weight concentration by the relative activity intensity to calculate daily mean exposure. We found activity intensity by matching ATUS activity codes with the Compendium of

Physical Activities (CPA), following Tudor-Locke et al. (2011) [175] (Tables C.2 and C.5). We then calculated the daily relative activity intensity for a given time and respondent ($I_{t,i}$ in Equation 2) with Equation 5.5.

$$I_{t,i} = \frac{MET_{i,a,t}}{\sum_{t=1}^{1440} t_i \times MET_{i,a,t}} \quad (5.5)$$

$MET_{i,a,t}$ is the MET value for activity a reported by individual i at time t (in minutes) in a given day.

5.3.7 Masking

We reflect filtration of fine particulate matter obtained by wearing a well-fitting mask in good condition. We use a TIL of 0.05 for an N95-type mask and 0.25 for a surgical type mask in line with testing by Steinle et al (2018) [204] and Langrish et al. (2009) [191]. Though various studies report mask-wearing behavior [219, 220], we did not have masking behavior specific to our temporal domain, temporal resolution, and study population. Instead, we treated $M_{t,s,i}$ as a scenario, reflecting either 0% or 100% compliance with various guidelines, further outlined below.

5.3.8 Pre- and Para-Pandemic Onset Eras

We defined the pre-pandemic era as January 2008 – March 2020. ATUS data collection was halted from mid-March 2020 – mid-May 2020. Thus, our pandemic period was from May 2020 – December 2020. We also considered other pandemic end-dates. While the

Public Health Emergency declaration related to COVID-19 was in place until May 2023, the ATUS data show that time use changes peaked long before then (Figure C.1). To investigate this uncertainty, we tested alternate para-pandemic periods of May 2020 to April 2021 and May 2020 to December 2022.

5.3.9 Interventions and Guidelines

We evaluate interventions that change the factors affecting $\text{PM}_{2.5}$, including outdoor air quality, infiltration, time-activity patterns, and masking. We use the same approaches – e.g., staying indoors or masking outdoors – from relevant national and international policies and guidelines related to air quality alerts, wildfire smoke, outdoor air quality, and indoor air quality. Rather than evaluate typical compliance, we test the limits of targeting each factor. For example, instead of only staying indoors during air quality alerts, or masking during wildfire events, we estimate the maximum potential reductions in exposure achieved by eliminating all time outdoors, or by always wearing a mask outside. For all cases, we use the pandemic period data to reflect the most recent time use, though we find little difference when using the pre-pandemic time use (Figures C.8 and C.9). The cases are summarized in Table 5.2, with further discussion following.

Previous work shows that Americans who adapt to poor outdoor air quality do so primarily by limiting their time outdoors. We have previously examined various levels of compliance with air quality alerts [162]. Here, we test the extreme case of eliminating all time outside, referring to this case as Indoor Only. We implement this by shifting all reported time spent Outdoors to Residential. Following recommendations by the American

Table 5.2: Strategies to reduce exposure.

Strategy	Case	Description
N/A	Base	Normal parameters (“Business as usual”) during the study period (Pre- or Para- pandemic).
Limit Time Outside	Indoor Only	Staying indoors to avoid outdoor pollution. All time in the Outdoor microenvironment is switched to Residential to identify the maximum benefit.
Wear Masks	Surg. Comm	Wearing a surgical mask in Commercial microenvironment.
	Surg Out	Wearing a surgical mask in Outdoor microenvironment.
	N95 Comm	Wearing an N95 mask in non-residential microenvironment, following pandemic procedures.
	N95 Out	Wearing an N95 mask in Outdoor microenvironment.
Reduce Infiltration	Res ACH Small	Normal behavior, but current Residential ACH values reduced by 25%.
	Res ACH Large	Normal behavior, but Residential ACH values are set to 0.5 (A reduction of approximately 47%).
Improve Outdoor Air Quality	Out Conc NAAQS	Mean daily outdoor concentrations over $9 \mu\text{g}/\text{m}^3$ are reduced to $9 \mu\text{g}/\text{m}^3$. Mean daily concentrations less than or equal to $9 \mu\text{g}/\text{m}^3$ are unchanged.
	Out Conc WHO	Mean daily outdoor concentrations over $5 \mu\text{g}/\text{m}^3$ are reduced to $5 \mu\text{g}/\text{m}^3$. Mean daily concentrations within $5 \mu\text{g}/\text{m}^3$ are unchanged.

Thoracic Society, we do not reduce the reported activity intensity [145].

We study several masking scenarios. First, we assess the effectiveness of masking in commercial environments, using an N95 or surgical style mask. This behavior, consistent with pandemic protocols, protects the wearer from $\text{PM}_{2.5}$ of outdoor origin as an ancillary benefit. Following guidelines for wildfire smoke events, we also evaluate wearing these same masks while outdoors. Again, with the aim of testing the limits of protection afforded by masks, we assume that study participants always wear these masks – well-fitting and in good condition – in the relevant microenvironments. We do not consider the case of Universal Face Mask Use (UFMU) – including Residences and Vehicles. We exclude it as this approach was not generally recommended in masking mandates or guidance to slow community-level transmission, except in public transit, though it was able to reduce household transmission [228].

We directly study adaptations aimed at reducing particle infiltration into residences. We consider reducing Residential ACH to 0.5, which results in an F_{INF} of around 0.4 using Equation 5.4 (Res ACH Large). Given the challenge of meeting this recommendation in the existing building stock, we present the results of the more commonly achieved air flow leakage reduction of 25% [229] (Res ACH Small) to achieve an F_{INF} of around 0.45. Further, we explore a theoretical range of residential infiltration values from 0 to 1 to examine its role in the effectiveness of moving indoors to reduce exposure in the pre- and para-pandemic eras.

Finally, we examine the value of reducing outdoor concentrations of $\text{PM}_{2.5}$. We examine the effect of compliance with the 2024 U.S. National Ambient Air Quality Standards

(NAAQS). This standard is a 98th percentile value of $35 \mu\text{g}/\text{m}^3$ over 24-hours, and mean of $9 \mu\text{g}/\text{m}^3$ annually [32]. To ensure strict compliance with the annual mean value over our eight-month para-pandemic period, we set all observed daily mean values that exceed $9 \mu\text{g}/\text{m}^3$ to $9 \mu\text{g}/\text{m}^3$. Similarly, we examine compliance with the much more stringent annual guideline of $5 \mu\text{g}/\text{m}^3$ set by the World Health Organization, restricting all daily mean values to the $5 \mu\text{g}/\text{m}^3$ threshold.

5.4 Results

5.4.1 Role of Pandemic in Factors Affecting Exposure to Outdoor Particulate Matter Pollution

People spent over 90% of their time inside buildings, as seen in Figure 5.1. Before the pandemic, people spent about 22 hours of their day (91.5%) inside buildings. Those 22 hours were split between residential buildings – 17.2 hours (71.8%) – and other buildings – 4.7 hours (19.7%).

During the pandemic, total time inside decreased only slightly (by 11.5 minutes) but shifted from Commercial to Residential environments during the day (Figure 5.1(a)), cutting total time in Commercial settings in half (Figure 5.1(c)). Similarly, as people stayed at home, time spent in vehicles during the morning and evening commute decreased, dropping time spent in Vehicles by one third (nearly half an hour).

Individual locations and activities affect exposure to $\text{PM}_{2.5}$ of outdoor origin. We find that about two-thirds of exposure to $\text{PM}_{2.5}$ of outdoor origin occurs at home (Figure 5.2(a)). This result agrees with prior studies accounting for time use and infiltration across

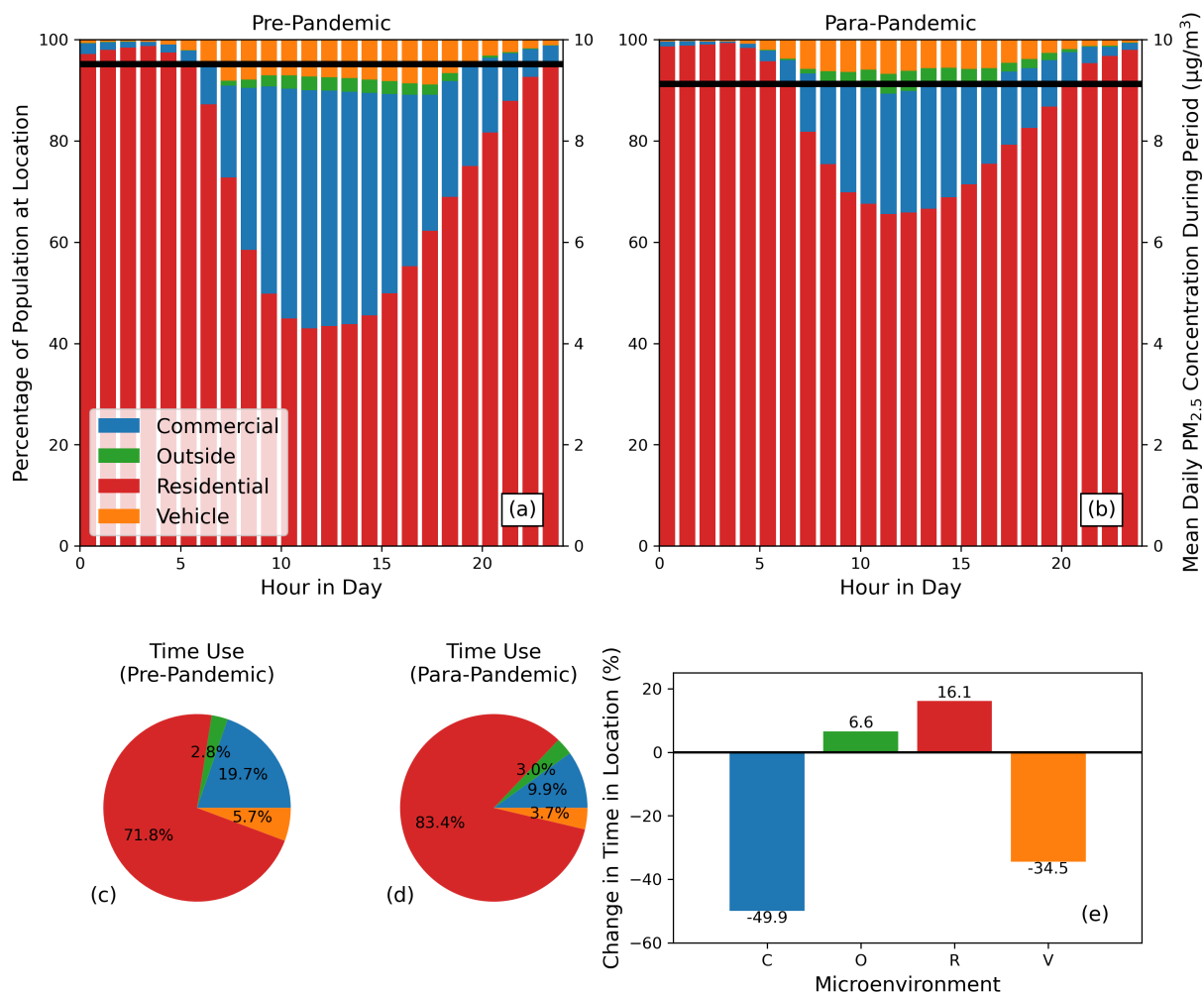


Figure 5.1: Location by microenvironment during pre- and para-pandemic periods (January 2008 to March 2020 and May to December 2020, respectively). (a) Percentage of the population within each microenvironment across all 24 hours of the day for (a) pre and (b) para-pandemic. The daily mean outdoor $PM_{2.5}$ concentration across the study area for each period is shown on the secondary y-axis of (a) and (b). Proportion of time spent in each microenvironment for entire (c) pre- and (d) para-pandemic period, with (e) corresponding percent change in time spent in each microenvironment after the pandemic onset.

microenvironments [144, 108]. This result is largely explained by the amount of time spent in residential settings. In our analysis, we also see greater particle infiltration in these settings than other buildings, on average (mean F_{INF} of 0.45 for Residences vs. 0.35 for Commercial). Counteracting this is a slightly lower activity intensity ratio for Residential ($I = 0.9$) vs. Commercial ($I = 1.0$) settings, as much of the time at home is spent asleep (Table C.6).

Outdoor time has a disproportionately large impact on daily exposure. People spend approximately 3% of their time Outdoors (Figure 5.1(c)(d)), but this time contributes to 11-12% of exposure (Figure 5.2(a)-(c)). This fourfold increase in exposure contribution compared to time spent arises because the outdoors offer no protection from outdoor air pollution, and because outdoor activities are more intense than the daily average ($I = 1.853$ pre-pandemic, and 2.076 para-pandemic (Table C.6)).

Similarly, the Vehicle microenvironment had a slightly larger impact on exposure than would be expected based on time use, though this discrepancy is driven more by the higher infiltration factor of the microenvironment ($F_{\text{INF}} = 0.6$) than activity intensity ($I = 1.3$).

Lastly, Commercial settings have a much lower exposure fraction than time fraction. This is due to their relatively low particle infiltration ($F_{\text{INF}} = 0.35$). The activity intensity in this environment resembles the daily average ($I = 1.0$ pre-pandemic and $I = 1.1$ para-pandemic).

During the pandemic, we find that exposures increased on average for non-maskers (Figure 5.2(d)). This result is driven by changes in time-activity patterns and ambient $\text{PM}_{2.5}$ concentrations, though they had opposite impacts on exposure.

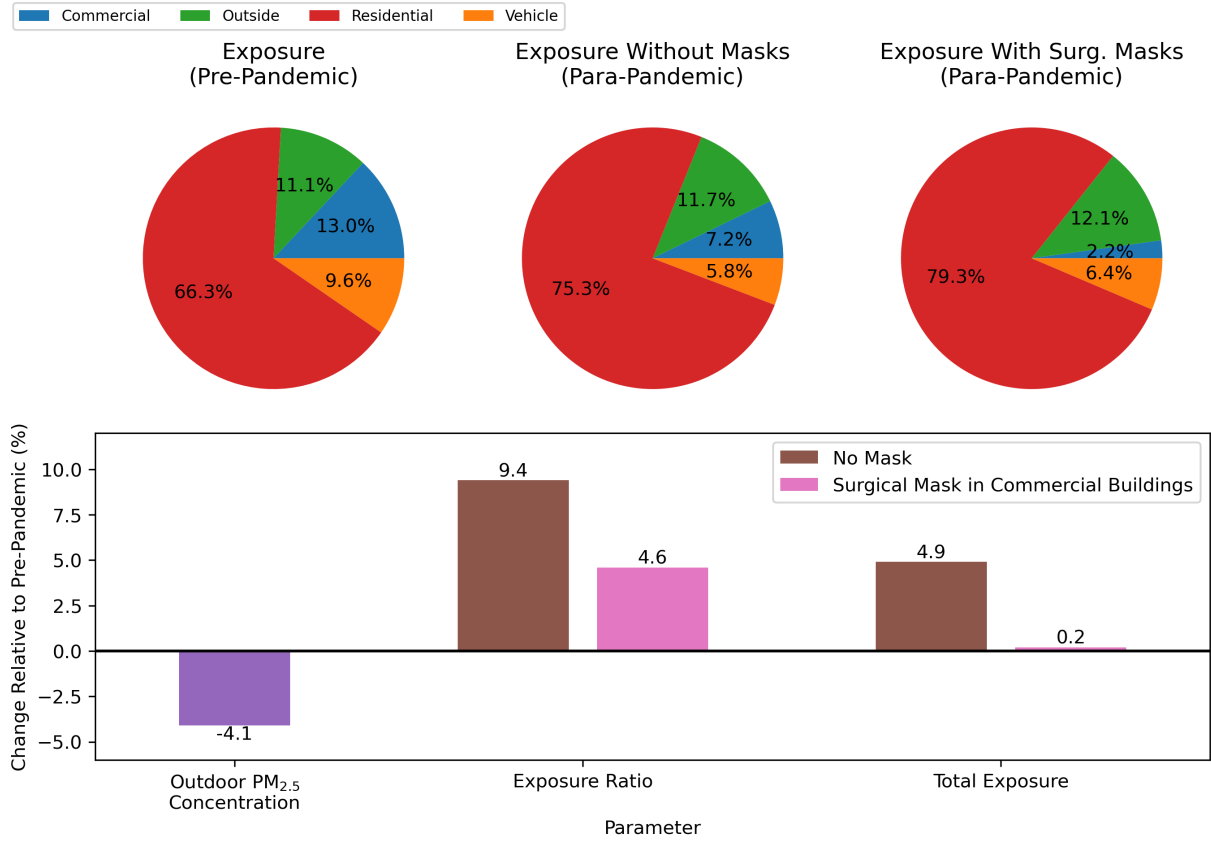


Figure 5.2: Exposure to PM_{2.5} of outdoor origin by microenvironment under different time use and behavior scenarios. (a) Pre-pandemic time use patterns. (b) Para-pandemic time use patterns without masking. (c) Para-pandemic time use patterns with the average individual wearing a surgical-style mask in non-residential indoor settings. (d) Percent change in outdoor PM_{2.5} concentration, exposure ratio, and total exposure of both para-pandemic masking scenarios relative to the pre-pandemic period.

Similarly to other work examining this pandemic period [213], we found daily mean outdoor PM_{2.5} concentrations decreased across the US by about 4% on average. We also estimated concentrations using the smaller available dataset of hourly concentrations, yielding slightly higher total exposures within 10% of those obtained with daily mean concentration

values (Figure C.4).

Beyond concentration, we assess the effect of other factors using the exposure ratio (Equation 5.2; Figure 5.2(d)). The exposure ratio weights outdoor concentration over the minutes of a day based on infiltration, activity intensity, and masking. Changes in these variables resulted in an exposure ratio increase of 9.4% for those who did not wear masks, and of 4.6% for those who wore masks in Commercial settings. The increased time in Residential settings boosted its contribution to exposure from 66% pre-pandemic to 75% during the pandemic for non-maskers. The contributions of Commercial and Vehicle microenvironments dropped accordingly, while the Outdoor contribution remained relatively stable.

The impact of behavioral changes outweighed the changes in outdoor concentration, causing an increase in average exposure even though outdoor concentrations decreased. The increase in total exposure was 4.9% for those who did not wear masks during the pandemic and 0.2% for those who did (Figure 5.2 (d)).

5.4.2 Variation of Exposure Changes with Occupation, Income, and Infiltration

Average exposures obscure significant variability, even across individuals living in the same area. We find differences in the pandemic's effects based on occupation, income, and infiltration.

We saw that time shifted away from Commercial settings during the pandemic, but not equally. This bifurcation in time use has been previously attributed to differences

in employment characteristics and family responsibilities [216, 218]. In our analysis, the percentage of people who spent less than 2 hours a day in Commercial microenvironments increased from 36% to 64% between the pre- and para pandemic periods. Conversely, the percentage of people who spent over 6 hours in Commercial microenvironments decreased from 42% to 22% between the pre- and para pandemic periods. Moving from 6 to 2 hours in Commercial microenvironments leads to an average increase in exposure ratio (R in Equation 5.2) of 5% for non-maskers, or 22% for maskers.

Occupational microenvironments affect exposure to $PM_{2.5}$ of outdoor origin. Outdoor workers are most exposed to outdoor $PM_{2.5}$ (with a pre-pandemic mean exposure of $5.6 \mu g/m^3$ compared to a national mean of $4.4 \mu g/m^3$). In addition to the greater time spent outdoors, they are also likely to inhale more air pollution because of the high activity intensity of their work. Exposure ratios for Outdoor workers were 0.689 and 0.693 for the pre- and para-pandemic periods respectively. These exposure ratios are higher than both Professional workers (0.579 and 0.639) and Service workers (0.589 and 0.629) for the pre- and para-pandemic periods. Healthcare workers, particularly those wearing effective masks, have among the lowest exposures to $PM_{2.5}$ of outdoor origin of any profession (a pre-pandemic mean of $3.8 \mu g/m^3$ for those wearing surgical masks at work) (Figure C.8).

The effect of the pandemic also differed by occupation. Figures 5.3(a) and (c) show the relative and absolute change in exposure ratio in three occupation categories: professional, service, and outdoors. The occupational categories are determined by occupation code and are summarized in Table C.2. The change in exposure ratio was highest among professionals (over 10% increase), followed by service industry workers (over 6%), and was negligible for outdoor workers (< 1% increase). ANOVA showed a statistically significant difference in

the pandemic’s effect on exposure ratio via occupation category, with a p-value of < 0.001 . This effect is due to the importance of occupation in determining exposure ratio, which also shows a p-value of < 0.001 in the pre- and para-pandemic periods.

Occupations that saw greater increases in telework also tended to have higher incomes. Thus, the associated exposure ratio grew more for higher-income individuals during the pandemic. Figure 5.3(b) shows a 50% increase in the relative difference in exposure ratio for the highest income decile compared to the lowest (from 10% to 15%), and a tripling between the highest decile and second-lowest (from 5% to 15%). The effect of income on the exposure ratio, and the exposure ratio difference due to the pandemic, was significant with a p-value $<< 0.001$.

Differences in residential infiltration can also create difference in exposure across individuals (Figure 5.4). Pandemic behavior changes led to exposure reductions for those with low Residential F_{INF} values (< 0.3) and increases for everyone else. For example, the average person in a tighter ($F_{\text{INF}} = 0.3$) house saw a negligible exposure change (0.1%) while the average person in a leaky ($F_{\text{INF}} = 0.7$) house saw an exposure change of 11%. Figure 5.4 (a) shows that differences in residential F_{INF} can lead to more than two-fold differences in daily $\text{PM}_{2.5}$ exposure, based on the available F_{INF} data (from $F_{\text{INFmin}} = 0.09$ to $F_{\text{INFmax}} = 0.64$, Figure C.5). A theoretical range of infiltration factors from 0 (perfectly airtight) to 1 (perfectly leaky) would yield an over four-fold difference in daily mean $\text{PM}_{2.5}$ exposure.

This also has implications for adaptation effectiveness, which is inversely related to infiltration. Figure 5.4(b) provides the percent exposure reduction achieved by trading all

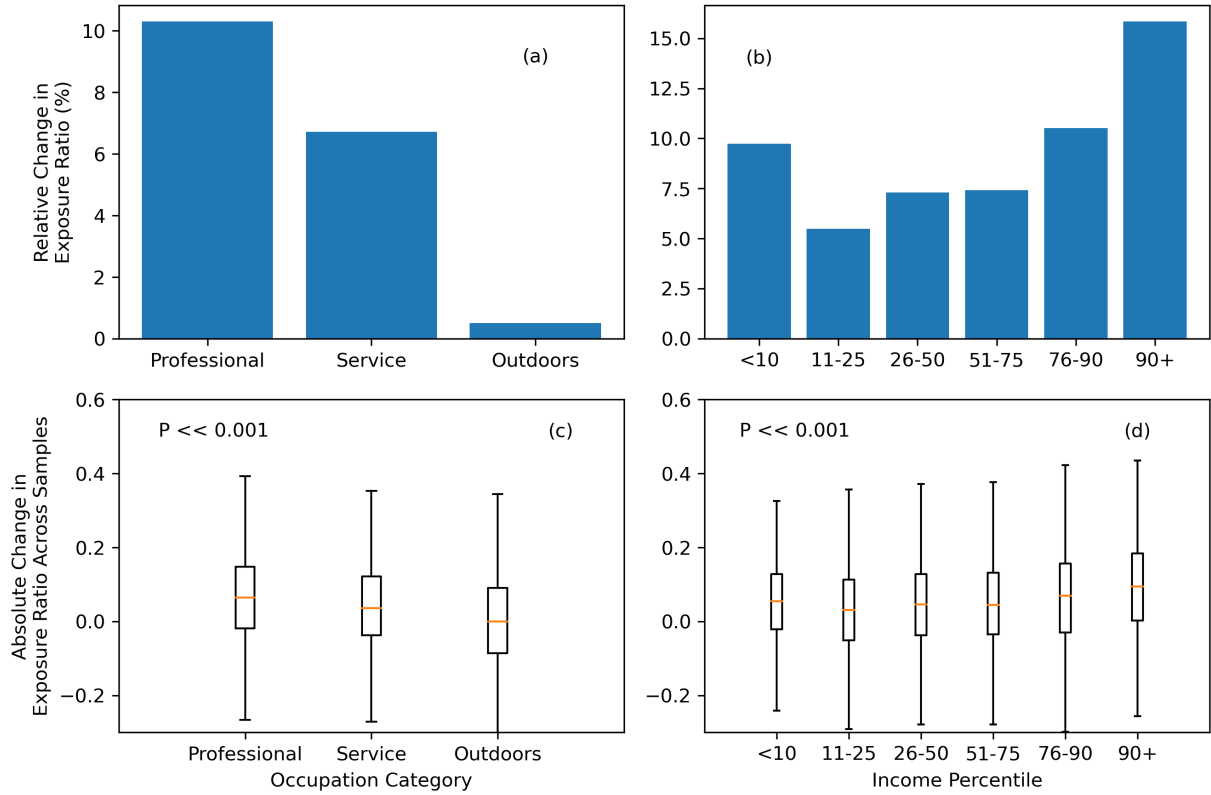


Figure 5.3: Pre- to post-pandemic change in exposure ratio by (a)-(c) occupation category and (b)-(d) income. Subplots (a)-(b) provide the percent change in the mean, while (c)-(d) show the distribution of the absolute change in exposure ratio. P-values are from ANOVA of occupation and income, respectively, in explaining pandemic's effect on exposure ratio.

outdoor time for residential time (termed avoidance adaptation). When people stay in leakier (high F_{INF}) houses to avoid polluted outdoor air, they see a smaller benefit than those in tighter homes. Before the pandemic, this ranges from 13% of exposure avoided for the most airtight buildings ($F_{INFmin} = 0.09$) down to 4% for the leakiest houses ($F_{INFmax} = 0.64$). The pandemic increases the role of infiltration on the effectiveness of avoidance adaptation. This relationship is shown in Figure 5.4(a) by the increased slope of exposure

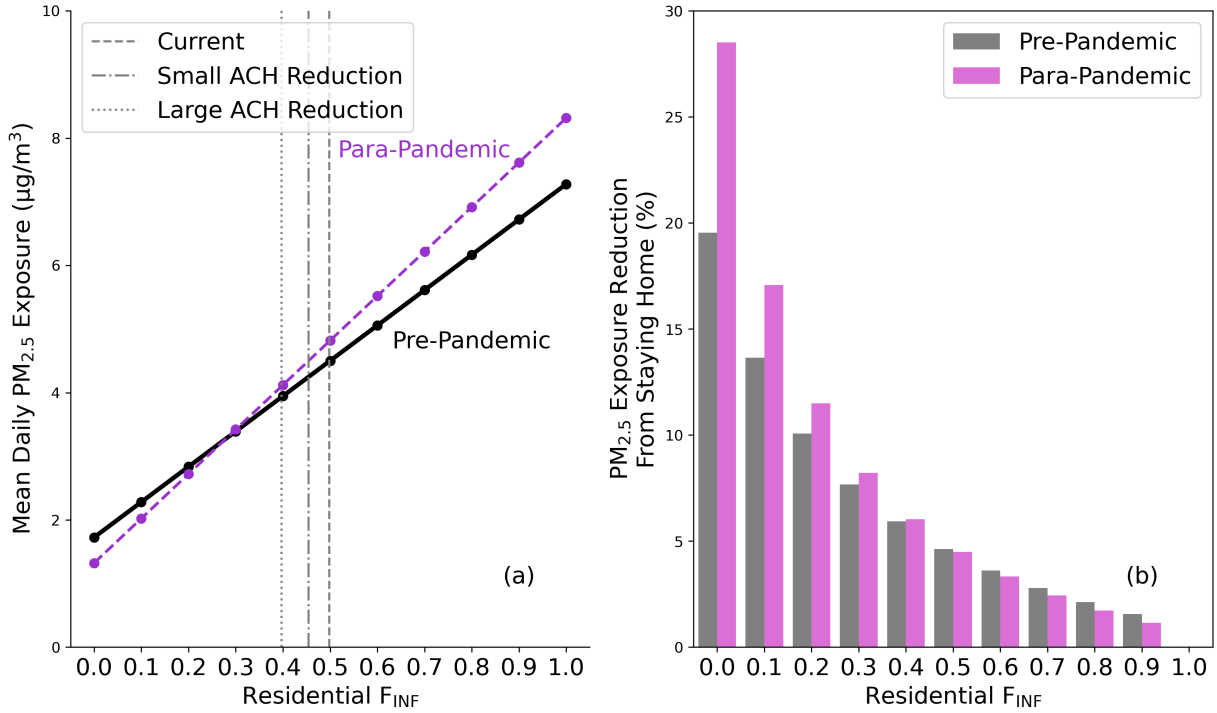


Figure 5.4: Variation of exposure to $PM_{2.5}$ of outdoor origin with residential infiltration (F_{INF}). (a) Variation of daily mean exposure in the pre- and para-pandemic periods (labeled Pre and Para, respectively). The particle infiltration corresponding to the current building stock is shown, along with potential improvements of airtightness by 25% (Small ACH Reduction), and reducing ACH to 0.5 (Large ACH Reduction). (b) Percent of exposure avoided by switching all outdoor time to residential time (termed “avoidance adaptation”) under the pre and para-pandemic periods.

with F_{INF} in the para-pandemic (purple) line compared to the pre-pandemic (in black). Per Figure 5.4(b), sheltering inside extremely airtight buildings ($F_{INF} < 0.1$) could reduce exposures by over 25% during the pandemic.

5.4.3 Effectiveness of Strategies to Reduce Exposure

Figure 5.5 shows that recommended adaptation strategies can reduce exposure to PM_{2.5} of outdoor origin. The most common adaptation strategy – staying indoors – offers little protection even when taken to the extreme: never going outside at all. This approach lowers daily mean exposure from 4.81 $\mu\text{g}/\text{m}^3$ to 4.45 $\mu\text{g}/\text{m}^3$, a decline of 7%. It eliminates the contribution of exposure while outdoors (from 11.7% to 0%), but transfers some of this exposure to the Residential microenvironment via infiltration (from 75% to 79%).

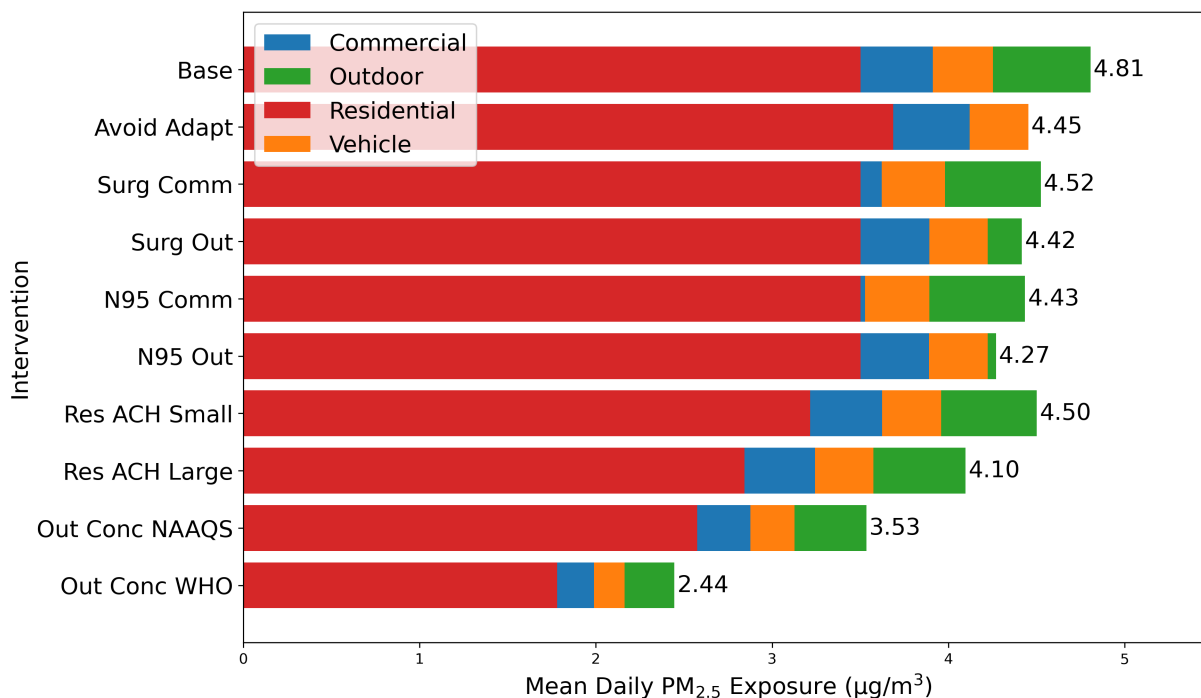


Figure 5.5: Mean daily PM_{2.5} exposure during the pandemic under different adaptation and mitigation scenarios. Includes contribution from each microenvironment.

Wearing masks can offer similar or greater protection than staying home. Wearing a surgical-style mask in Commercial settings reduces exposure to outdoor PM_{2.5} nearly

as much as never going outside (decline of 6%). Improved masking, e.g., always wearing N95-style masks outside, reduces exposure by 11%; keeping these masks on in Commercial settings, too, offers a total reduction of 19% (down to $3.9 \mu\text{g}/\text{m}^3$).

Without resorting to Universal Face Mask Use, achieving greater exposure reductions requires tackling Residential Buildings, the microenvironment contributing the most to total exposure. Reducing infiltration leads to an overall exposure reduction of up to 15% under the large reduction scenario. This benefit is larger than avoidance adaptation or the masking scenarios shown in Figure 5. It is only exceeded by masking in both outdoor and commercial environments, which is the additive effect of the Comm and Out scenarios in Figure 5.5.

Reducing outdoor concentrations offers the largest reduction in exposure, up to 50%. This is the only approach to reduce exposure to $\text{PM}_{2.5}$ of outdoor origin across all microenvironments. By restricting daily outdoor concentrations to $9 \mu\text{g}/\text{m}^3$, our mean concentration across our study area over the para-pandemic period drops from $9.12 \mu\text{g}/\text{m}^3$ to $6.69 \mu\text{g}/\text{m}^3$. This in turn reduces mean daily exposures by over 25% (from 4.81 to $3.53 \mu\text{g}/\text{m}^3$). Meeting the stricter WHO guideline lowers our mean outdoor concentration to $4.63 \mu\text{g}/\text{m}^3$, lowering exposure by nearly 50% (down to $2.44 \mu\text{g}/\text{m}^3$).

These findings are subject to uncertainty. Sensitivity analysis of parameters reflecting buildings, behavior, and the pandemic duration reveal that our main analysis may understate the effects of the pandemic on exposure. First, we examine the considerable uncertainty [179] in the penetration factor of $\text{PM}_{2.5}$ through the building envelope (termed “P” in Equation 5.4). Increasing P to another previously published value of 0.9761 exacer-

bates the effect of the pandemic on exposure, leading to higher calculated exposures under the higher infiltration rates (Figure C.6). Another source of uncertainty was the ATUS activity data. While the responses are generally highly detailed, some reported activity locations are vague and are difficult to classify as occurring either indoor or outdoor (e.g., activity number 120101 “Socializing and communicating with others”). In our base case, we classified these activities as Indoors. If, instead, we assign Unknown time to Outdoors, we see the same directional changes for time-use and exposure (Figure C.7). The overall effect of the pandemic on exposure is exacerbated by spending more time outside, rising from a 5% increase to a 8.7% increase for non-maskers. However, this 8.7% increase is likely an upper bound, given that other estimates of outdoor time show it to be limited [100].

Recognizing the lack of consensus in the literature about the end date of pandemic-driven behavior change, we analyzed alternative “para-pandemic” periods up to the end of 2022 (Figures C.2-C.3). These figures show activities trending towards their pre-pandemic values, but not fully returning. We saw the greatest impact of the pandemic when we considered May 2020-December 2020. Other pandemic periods considered were May 2020-April 2021, which yielded an exposure ratio increase of 8.1% and an exposure increase of 2.3% for non-maskers. Using the most recent data available, up to December 2022, the exposure ratio for the longer-pandemic period still shows a 7.2% increase relative to the pre-pandemic period. Fortunately, however, the concentration drop deepens to 7.5%, such that the average exposure change becomes negligible compared to pre-2020 levels.

5.5 Discussion

This study agrees with previous work showing that (1) most exposure to $\text{PM}_{2.5}$ of outdoor origin happens in residences; (2) the pandemic affected a variety of factors that influence this exposure; and (3) multiple interventions enshrined in current guidance can reduce exposure, including moving indoors, masking, reducing infiltration, and reducing outdoor concentrations. It builds on prior work by (1) estimating how the pandemic influenced exposure and (2) directly comparing the resulting effectiveness of different interventions to reduce exposure.

We find that average exposure to $\text{PM}_{2.5}$ of outdoor origin likely increased during the pandemic for non-maskers. This result is driven by the combination of pandemic-driven changes in factors including time-activity patterns and ambient $\text{PM}_{2.5}$ concentrations, in addition to masking.

Our work agrees with prior studies showing that outdoor $\text{PM}_{2.5}$ dropped during the pandemic. Many estimates focused on the initial lockdowns, finding a 3-21% decrease in outdoor mass concentrations [209, 210, 211]. However, Bekbulat et al. (2021) did not see a decrease in national mean $\text{PM}_{2.5}$ during the lockdown period, and only found modest reductions in other criteria air pollutants [208]. We found that outdoor $\text{PM}_{2.5}$ concentrations decreased by 4% for our study population over the para-pandemic period (May 2020 – December 2020) relative to pre-pandemic (January 2008 – March 2020). In the closest study to ours in spatial and temporal domain, He et al. (2024) found a 3-4% decrease in national population-weighted annual mean $\text{PM}_{2.5}$ over April 2020 to March 2021 [213], which is well aligned with our observed 5.4% mean concentration reduction

from May 2020 to April 2021 (Figure C.2 (g)).

Despite this reduction in outdoor $\text{PM}_{2.5}$ during the pandemic, we find time use shifted to environments with higher infiltration, potentially resulting in higher exposures. Specifically, more time was spent in residential environments with higher expected particle infiltration than commercial environments, in compliance with stay-at-home orders and increasing work-from-home behavior.

Consequently, the residential microenvironment gained in importance over the pandemic, from a 66% contribution to exposure, to 75% (non-maskers) or 79% (maskers). Our estimates of the contribution of each microenvironment to exposure to $\text{PM}_{2.5}$ of outdoor origin align well with prior work. Pre-pandemic, our exposure contributions by microenvironment were 66% Residential, 13% Commercial, 11% Outdoor, and 10% Vehicle. Similarly, Azimi and Stephens (2020)'s exposure results for $\text{PM}_{2.5}$ of outdoor origin found contributions of 67% for Residential, 18% Commercial, 11% Outdoors, and 4% Vehicles [144]. Fisk and Chan (2017) account for exposures across microenvironments. Their reported time use, inhalation rates, and infiltration factors imply exposure percentages of 63%, 13%, 17%, and 7% across the Residential, Commercial, Outdoors, and Vehicle microenvironments, respectively [108]. All studies agree that the Residential microenvironment accounts for approximately two-thirds of outdoor-generated $\text{PM}_{2.5}$ exposure, with Vehicles offering the lowest contribution, and Commercial and Outdoor between 11%-17%. Differences are explained in part due to time use data, with prior work using the National Human Activity Pattern Survey (NHAPS) conducted from 1992-1994 reported in Klepeis et al. (2001) [100].

Time-use changed significantly during the pandemic period. Our results on this shift align with prior work. Restrepo and Zeballos (2022) also analyzed ATUS data and found increased time spent working from home, and reductions in other activities such as work-related travel, shopping, shopping-related travel, and eating away from home [214]. These changes reflect the increase we found in Residential microenvironments and decrease in time spent in Vehicle and Commercial microenvironments. A study by Shi and Goulias (2024) examined the lasting impact of the COVID-19 pandemic on time use and activity patterns and found that time spent traveling decreased by 30% from 2019 to 2020, which aligns closely with our pre-pandemic to para-pandemic drop of 34.5% [215].

The effect of the pandemic’s time-use changes was to potentially increase exposure, on average, with significant individual variation. Masking in non-residential spaces likely offered an important counterbalance to time-use changes during the peak period of the pandemic, during which 70% to over 80% of U.S. adults wore masks [230, 231]. However, since the winter of 2021, mask-wearing has declined sharply in the U.S. [219], while, we find, many exposure-enhancing time-use changes have persisted through 2022.

Those who increased their time in residences saw greater average exposures. These were primarily higher-income workers in professional occupations. Medical professionals who wore masks in well-ventilated buildings potentially experienced the smallest effect of the pandemic on $\text{PM}_{2.5}$ exposure. This pattern with income is the opposite of that for COVID-19 itself, where low-income and front-line workers suffered higher exposures and outcomes related to COVID-19 [217, 232].

However, this effect may be mediated by housing quality. Important equity implications

stem from the disproportionately large ambient $\text{PM}_{2.5}$ exposures that are experienced by those in leakier housing (higher by a factor of two or more). Lower incomes are associated with older, leakier housing [233, 105] and thus higher infiltration rates. By increasing time spent at home, the pandemic exacerbated these exposure inequalities.

The confluence of competing factors determining exposures also has implications for interventions. The effectiveness of behavioral interventions to reduce exposure – like masking, or staying indoors – depend on uptake, duration, and individual factors, like occupation and residential infiltration. The most common behavioral intervention – staying indoors – offers limited protection. The case of the pandemic showed that spending more time at home can increase exposures even as outdoor pollution levels drop. The most extreme case – eliminating all outdoor time across our study population – was among the least effective interventions at reducing exposure to outdoor air. This demonstrates the limitations in relying in individual, short-term adaptation to reduce health risks.

The effectiveness of avoidance adaptation is also strongly tied to the infiltration factor of people’s residence. Building scale interventions to reduce infiltration only reduce exposure in the Residential microenvironment. Nonetheless, the large amount of time spent in that microenvironment means that reductions there lead to sizable reductions in overall exposure. In our analysis, reducing Residential ACH values to 0.5 offered the largest exposure reduction of any other single adaptation measure. Reducing building leakage can also improve energy efficiency, thereby reducing cooling demand and associated health risks from air pollution under climate change [137, 234]. However, retrofits can fail at reducing infiltration [229], and, even if successful, infiltration varies with occupant behavior [235]. Increasing airtightness to reduce infiltration must be implemented carefully, or it can trap

indoor-generated pollutants like $\text{PM}_{2.5}$ associated with cooking [236]. Our analysis of ATUS data shows that time spent on related activities like “food and drink preparation” and “kitchen and food clean-up” increased about 14%, from 37 minutes a day to 42 minutes per day. Thus, any effort to reduce infiltration should address ventilation and filtration.

Mask wearing strategies could be equally effective as reducing building infiltration, especially with high quality masks worn outdoors. Masking is more flexible, allowing people to engage in most normal activities. It is also inexpensive on a cost-per-use basis. However, though the Chinese population might spend \$600,000 USD on facemasks during severe pollution episodes [237], in North America, masks have low uptake levels due to non-market effects, including physical discomfort, social norms, and political and ideological beliefs [238, 239]. In addition, their rated TIL, used herein, may overstate their effectiveness at reducing $\text{PM}_{2.5}$ exposure in real-world conditions [186].

All adaptation strategies rely on individual awareness and compliance (e.g., wearing masks, staying indoors, keeping the indoor environment clean). Mitigation – reducing outdoor concentrations – is robust to the behavior of the exposed population, instead placing the onus on emitters. Keeping outdoor air within recommended concentration guidelines was the most effective approach to reduce exposures. Such reductions are known to particularly benefit vulnerable and racialized populations [61].

5.5.1 Limitations

By adding factors beyond the change in concentration, we attempt to improve on exposure estimates used in previous studies evaluating the change in health risks from air pollution

during the pandemic. However, our estimated mean exposure is not dose, which would be more directly linked to health outcomes. Based on the increase in absolute activity intensity during the pandemic, the change in inhaled dose would be even higher than the change in mean exposure presented here. Those estimates would be improved with individual concentrations measured at the same locations and frequencies of individual activities across all ATUS respondents, instead of our subsample. More detailed activity and building data could improve estimates of infiltration by microenvironment, especially for non-residential buildings and vehicles. Empirical studies should assess whether changes in observed incidence rates varied with these modeled exposure changes, given individual behaviors, including adaptation. We considered a subset of potential adaptation strategies, reviewed elsewhere [164].

5.6 Conclusions

The majority (over 90%) of exposure to outdoor air pollution occurs in residential, commercial, and vehicle microenvironments. Most (66%) exposure to $\text{PM}_{2.5}$ occurs within residential environments. The COVID-19 pandemic only strengthened the importance of this microenvironment (to $> 75\%$) as people spent more time at home.

Greater time spent in relatively leaky homes, with higher infiltration of outdoor $\text{PM}_{2.5}$, meant that population exposure to $\text{PM}_{2.5}$ of outdoor origin likely increased by 5% (for non-maskers), even as outdoor concentrations decreased by 4% on average.

Exposure increases were higher for those in high-income, professional occupations, and for people living in leakier-than-average homes. Those who followed public health guidance

to reduce COVID-19 transmission by wearing masks in public indoor spaces also received protection from PM_{2.5}.

Many strategies to reduce transmission risks of COVID-19 also reduce exposure from PM_{2.5}, including masking and improving indoor air quality. Since the pandemic increased the time people spent at home, residential air quality has become valuable as a possible method of adaptation to poor outdoor air. Assuming no increase in PM_{2.5} concentrations due to indoor sources, reducing the infiltration of outdoor PM_{2.5} in residences provides similar protection to masking, and boosts the protection achieved by complying with air quality alerts. The greatest exposure reductions, however, and the only ones robust to adaptation behaviors, are earned by meeting international standards for outdoor air quality set by the World Health Organization.

These results emphasize the importance of individual factors when designing interventions to reduce exposure to outdoor air pollution. They show the potential synergies of overlapping multiple strategies, including those which are short-term (staying indoors), long-term (building retrofits), flexible (masking), and robust (improving outdoor air quality). Future work should employ more comprehensive, individual evaluations of dose, further evaluate behavioral interactions and feedbacks between strategies, and consider a wider range of specific interventions.

Chapter 6

Conclusion

6.1 Summary of Contributions

The work included in this dissertation helped address the research gaps identified in Section [2.7](#). Contributions from each study are listed below.

Chapter [3](#)

- Knowledge: First paper to evaluate the effects of climate change on air quality alerts due to $PM_{2.5}$, finding conditions for alerts could quadruple on average across the U.S. by 2100.
- Methods: First paper to introduce multiple models of adaptation to air quality alerts, including rational actor, threshold, and social learning, all of which demonstrate that adaptation can offer limited protection from the climate penalty on air pollution.
- Implication: Demonstrates that, without additional policy, adaptation will offer limited protection; however, even under deep carbonization, enhancing adaptation can reap net benefits.

Chapter 4

- Knowledge: First paper to study the climate penalty impact on air quality alerts due to ozone. Found conditions for alerts are likely to double in the U.S. by 2100.
- Knowledge: First study to present adaptation benefits by age group. Found that benefits for seniors are significantly higher than for younger populations.
- Methods: First paper to quantify the benefits of adaptation by considering exposure to ambient PM_{2.5} and ozone across multiple microenvironments.
- Implication: The populations at highest risk of health impacts from air pollution could greatly benefit from targeted approaches. Specifically, more relevant recommendations, at different thresholds, communicated through channels they use, could reduce air pollution exposure and mitigate adverse health outcomes.

Chapter 5

- Knowledge: First paper to consider effects of both outdoor concentration and behavioral changes to assess the effect of the COVID-19 pandemic on exposure to PM_{2.5} of outdoor origin; found that exposure increased even though outdoor concentrations decreased.
- Methods: First study to quantify PM_{2.5} exposure based outdoor concentration, time-activity patterns, masking, and building infiltration across four microenvironments during regular activity, pandemic activity, and adaptation.

- Implication: Individual factors heavily influence people’s exposure to PM_{2.5} and must be considered in interventions meant to reduce exposure to air pollution.

6.2 Limitations and Recommendations for Future Work

While this work provides new, valuable insight into the benefits of air pollution adaptation and climate change mitigation, there are some limitations that must be acknowledged. First, our models of future pollutant concentrations assume that anthropogenic emissions remain constant. This is helpful to isolate the climate penalty - the effect that climate change has on air pollution - but it leads to higher than expected pollution concentrations in climate mitigation policy scenarios. This occurs because, if sources of GHGs are removed, the pollutants co-emitted alongside them are also removed. Also, the effect of wildfire pollution is not captured in our integrated modeling framework. Both of these factors lead to potential underestimates of the benefits of climate change mitigation policy.

Another limitation, as this research was conducted in Canada, is that the study domain is the U.S. This changes many of the study parameters (population health, activity choice, pollution levels, building stock, air quality alert method). However, other research has modeled the effect of the climate penalty on future air pollution concentrations in Canada [41]. While not in the scope of this dissertation research, we plan to extend the exposure and adaptation models developed in this research to Canada, to give local policy-relevant insights.

There are a few different paths that future work in this area could take. One direction is improving total air pollution exposure representation. My work showed the value of

accounting for ambient pollution exposure across different microenvironments. However, due to the variability of indoor generated pollution, my analysis was limited to pollutants of outdoor origin. For adaptation to be effective, and to minimize overall daily exposure, indoor pollutant concentrations should be known and minimized. Future work could use monitor-based indoor pollution concentrations to better characterize indoor pollutant generation patterns. This could help improve adaptation guidance, with an ultimate goal of providing personal recommendations based on people's unique activity patterns and microenvironment characteristics.

Further work should also consider the broader societal implications of adaptation. Avoidance adaptation requires staying indoors, which may have adverse mental and physical health effects. High adaptation demand also means that populations recognize the threat of environmental hazards. Populations who experience and are aware of environmental hazards may be more demanding of regulatory intervention to protect their health. The emergence of this desire for long-term change under future pollution levels should be studied.

Adaptation to air pollution also affects exposure to other environmental hazards. For example, people may want to close their windows to protect against summer wildfire smoke but find that they become uncomfortably hot. In this scenario, they are reducing exposure to air pollution but becoming more vulnerable to heat impacts. Conversely, people may choose to move activities from outdoor to indoor because of heat-related discomfort. In this scenario they are altering their exposure to air pollution. This could be a protective effect if indoor pollution levels are lower than outdoor. The synergistic impact of higher temperatures and pollution concentrations under climate change merits future study, particularly

to understand their implications for adaptation.

In summary, reducing exposure to air pollution remains an exciting research field with plenty of opportunity to contribute and protect people's health!

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APPENDICES

Appendix A

Supplemental Information for “Health and Equity Implications of Individual Adaptation to Air Pollution in a Changing Climate”

A.1 Projection Into Future

When running the model in the years 2050 and 2100, the proportion of adapters is initialized to the last values from the previous time period. For 2050, the proportion of adapters from 2020 taken from the historical fitting process is used. Additionally, population and economic values are adjusted for predicted future growth, which are period and sometimes policy dependent and summarized in Tables [A.6](#) through [A.9](#).

A.2 Comparison to Start-of-Century

Table A.10 compares PM_{2.5} exposure, adaptation days, exposure reduction per adaptation, adaptation benefits, adaptation costs, and adaptation net benefits between different policy/time period combinations and the beginning of the 21st century. Table A.10 shows that in both the REF and P3.7 scenarios, exposure to PM_{2.5} without adaptation will increase by the year 2050. P3.7 reduces the climate penalty on PM_{2.5} pollution by approximately half at 2050 and maintains pollution levels throughout the remainder of the century. Under REF, PM_{2.5} exposures continue to rise, leading to a climate penalty that is over five times worse than P3.7. Rational adaptation is shown to mitigate PM_{2.5} exposure in the future. At 2050, rational adapters would, on average, adapt 27 more days per year than they would under REF and 25 more days per year than they would under P3.7. This increase in adaptation is caused by higher PM_{2.5} pollution concentrations and an older population who will be more strongly affected by PM_{2.5} pollution. We see that these populations are willing to adapt when pollution reductions per adaptation day are lower than they would be at the start-of-century. The adaptation benefits, costs, and net benefits show that adaptation net benefits are highest in the REF scenario when pollution levels are highest and decrease under stringent climate policy.

A.3 Quantifying the Comparison to Previous Research

The most similar previous research to this is Buonocore et al. (2021), who investigated the potential health benefits of air quality alerts [17]. Buonocore et al. (2021) consider both long- and short-term mortality risk changes due to ozone and PM_{2.5} in the population

aged 65 years and older. When the Air Quality Index exceeds 100, assuming no infiltration or offsetting indoor sources, they find per capita benefits to be no higher than \$14 per person per hour. Here, we find an average benefit of \$31 per person per hour for adults aged 30 and over at the start-of-century across the U.S. Several differences in study design help to explain this difference; however, the dominant factor is the treatment of exposure reduction. Buonocore et al. allows a single hour of adaptation per day between 6 am and 9 pm, with exposure to outdoor air at all other hours of the day. This leads to differing exposure reductions based on how much worse the most polluted hour is than the other 23 hours. Our adaptation model, due to using 24-hour mean concentrations and accounting for exposure differences indoors and outdoors, results in a constant exposure reduction of approximately 15%. In Buonocore et al. (2021), to achieve that level of reduction, the worst hour would have to be four times higher than the average of the remaining 23 hours. When we reproduce Buonocore et al.’s findings but with our exposure reduction assumptions, we find up to a 1.5-fold (or 50%) increase in benefits.

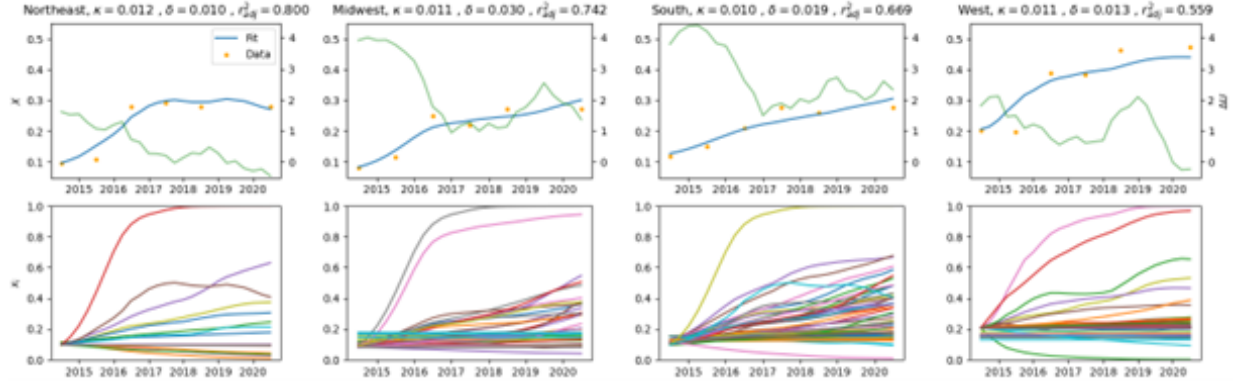


Figure A.1: Best fit for Social Learning Model parameters based on fitting to SummerStyles survey data by region [5]. Top row of plots show the national proportion of adapters based on survey data along with the modeled best fit and difference in utility between adapters and non-adapters. The bottom row of plots show the proportion of adapters by grid cell over the fitting period (2014-2020).

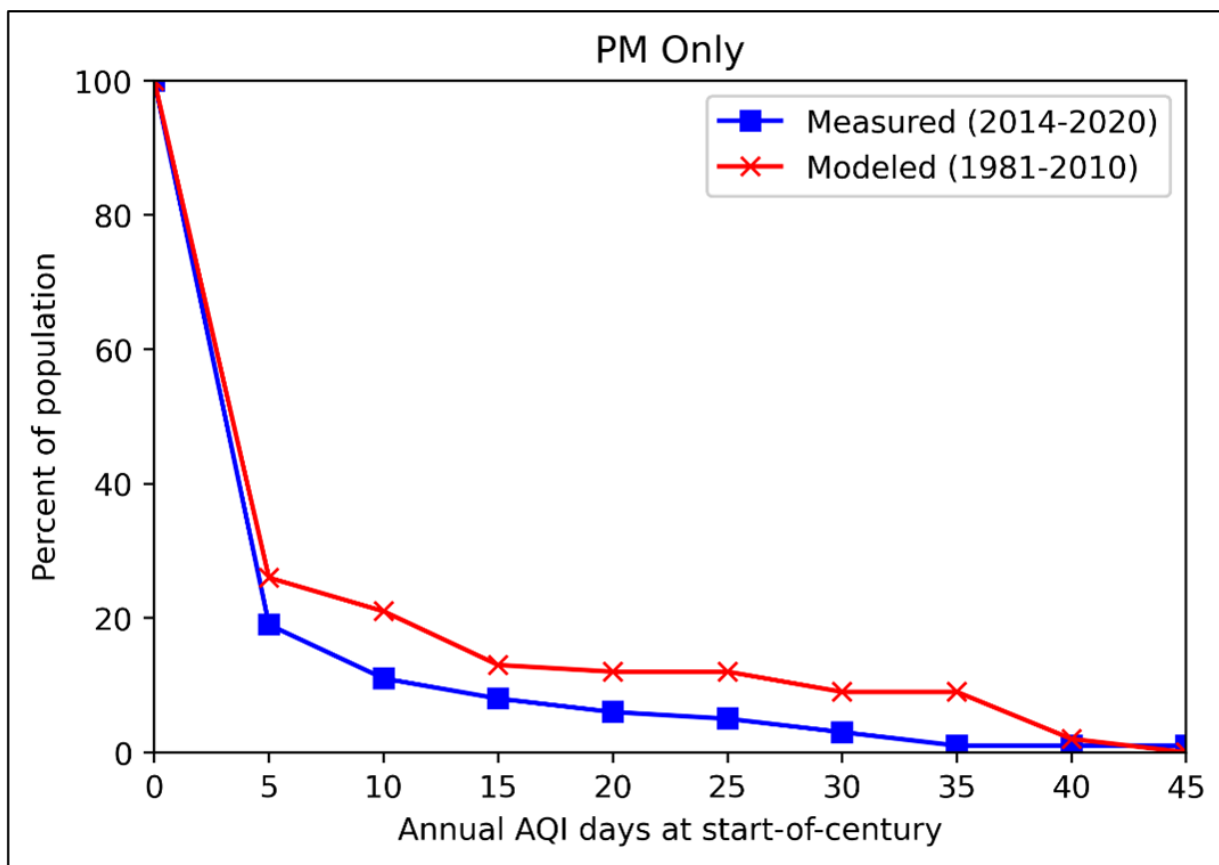


Figure A.2: Comparison of modeled AQI days vs measured AQI days. Measured AQI days based on $\text{PM}_{2.5}$ concentrations from US EPA monitors interpolated with Voronoi neighbor averaging performed in BenMAP-CE.

Table A.1: U.S. EPA guidance for PM-driven AQI. Adapted from the “Technical Assistance Document for the Reporting of Daily Air Quality – the Air Quality Index (AQI)” document [6]

AQI Range	Category	PM _{2.5} Range ($\mu\text{g}/\text{m}^3$)	U.S. EPA Guidance
0 - 50	Good	0-12.0	None.
51 - 100	Moderate	12.1 - 35.4	Unusually sensitive people should consider reducing prolonged or heavy exertion.
101 - 150	Unhealthy for Sensitive Groups	35.5 - 55.4	People with heart or lung disease, older adults, children, and people of lower socioeconomic status should reduce prolonged or heavy exertion
151 - 200	Unhealthy	55.5 - 150.4	People with heart or lung disease, older adults, children, and people of lower socioeconomic status should avoid prolonged or heavy exertion; everyone should reduce prolonged or heavy exertion.
201 - 300	Very Un- healthy	150.5 - 250.4	People with heart or lung disease, older adults, children, and people of lower socioeconomic status should avoid all physical activity outdoors. Everyone else should avoid prolonged or heavy exertion.
301 - 500	Hazardous	250.5 - 500.4	Everyone should avoid all physical activity outdoors; people with heart or lung disease, older adults, children, and people of lower socioeconomic status should remain indoors and keep activity levels low.

Table A.2: Parameter definitions for the Rational Actor Model.

Name	Description
NB_d	Net benefits of adapting on day d.
B_d	Benefit of adapting on day d.
C_d	Cost of adapting on day d.
VSL	Value of a Statistical Life. Calculated from the willingness to pay to reduce risk of death, with risk reduction normalized to 1.
I_d	Change in annual mortality incidence rate due to adaptation on a given day.
Y_o	Population baseline mortality rate.
RR	Relative Risk. The increase in incidence rate of an adverse health outcome (mortality in this study) that can be attributed to a 10 $\mu g/m^3$ rise in $PM_{2.5}$ concentration.
$\Delta PM_{2.5a_d}$	Change in annual 24-hour mean $PM_{2.5}$ concentration after adaptation on day d.
$PM_{2.5a}$	Average annual outdoor concentration of $PM_{2.5}$ with no adaptation.
$PM'_{2.5a_d}$	Equivalent annual outdoor concentration of $PM_{2.5}$ after adaptation on day d.
$PM_{2.5d}$	24-hour mean outdoor $PM_{2.5}$ concentration on each adaptation day d.
$PM_{2.5n}$	24-hour mean outdoor $PM_{2.5}$ concentration on each non-adaptation day n.
ψ	Adaptation exposure reduction factor.
T_{in}	Average daily time spent indoors. 23 hours for default case.
T_{out}	Average daily time spent outdoors. 1 hour for default case.
F_{INF}	Infiltration Factor. Represents the fraction of outdoor $PM_{2.5}$ that enters indoors and remains airborne.
ϕ	Hourly adaptation cost. Default parameterization for a grid cell is that grid cell's mean hourly wage.
T_{adapt}	Time spent adapting in hours. For Rational Actor model, this is set equal to T_{out} to maximize net benefits of adapting.

Table A.3: Parameter definitions for the Social Learning Model.

Name	Description
x_i	Proportion of adapters in grid cell i.
$1 - x_i$	Proportion of non-adapters in grid cell i.
U_{A_i}	Utility of being an adapter.
β_i	Cost of adaptation.
δ_r	Weight of social norms in U.S. census region r.
$\omega(x_i)$	Function to determine social norms.
U_{N_i}	Utility of being a non-adapter.
R_i	Function that represents the portion of perceived risks of air pollution that are mitigated by adapting.
ΔU_{it}	The difference in utility between being an adapter and a non-adapter.
R_0	Empirically fitted constant added to scale the difference between mitigated perceived risk and cost to a comparable unit to the influence of social norms.
$\tilde{x}_{it+1}$	Raw proportion of adapters in grid cell i one time step into the future. Gets bound by minimum and maximum values.
x_{it}	Proportion of adapters in grid cell i in the current time step.
κ_r	Social learning rate for U.S. census region r.
σ_i	Parameter related to the population in grid cell i. Higher values mean more population.
SCI_{ij}	Social Connectedness Index between grid cells i and j. Determines weight of social norm influence between the two grid cells.
β_{it}	Cost of adaptation in grid cell i at time t.
ϕ_i	Mean hourly wage in grid cell i.
T_{adapt}	Daily time that the population spends adapting.
ξ_r	The portion of Tout that the population switches to Tin when adapting.
ρ_{it}	The proportion of days with AQI over the relevant threshold (100 or 150) in a grid cell i at time t.
s	An empirically fit scaling factor relating perceived risk to actual risk.
M_{it}	Represents the economic value of the severity of risk of premature death due to PM _{2.5} pollution in grid cell i at time t.
η_{it}	The proportion by which adapters reduce their PM _{2.5} exposure in grid cell i and time t.
VSL	The Value of a Statistical Life. Determined by a population's willingness to reduce their risk of premature death.
$\tilde{M}_{it}$	The incidence of PM _{2.5} driven premature mortality for a population of non-adapters.
ψ	Ratio of exposure under adaptation to exposure under non-adaptation time use.
F_{INF}	Fraction representing the portion of outdoor PM _{2.5} that penetrates the building envelope and remains suspended indoors.

Table A.4: Portion of health burden valuation driven by PM_{2.5} mortality. Calculated by isolating the valued health burden from PM_{2.5} mortality and dividing that by the total health burden from PM_{2.5} and O₃. Data for calculations are in Saari et al. (2019) [7].

Year	P3.7
2050	94.68%
2100	93.20%

Table A.5: Parameters used for Social Learning Model. These parameters (except for T_{out} , which was determined based on previous studies) are empirically fit through the process described.

Name	Description	Value
s	Scaling factor for risk	1
R_0	Baseline risk perception (\$ USD 2000)	446
ξ_n	Proportion of outdoor time adapters choose to stay in-doors in Northeast	0.7949
ξ_m	Proportion of outdoor time adapters choose to stay in-doors in Midwest	0.7749
ξ_s	Proportion of outdoor time adapters choose to stay in-doors in South	0.8492
ξ_w	Proportion of outdoor time adapters choose to stay in-doors in West	0.7047
T_{out}	Average time spent outdoors for non-adapters (hours/day)	1
κ_n	Social learning rate for Northeast census region	0.01205
κ_m	Social learning rate for Midwest census region	0.01160
κ_s	Social learning rate for South census region	0.01001
κ_w	Social learning rate for West census region	0.01172
δ_n	Strength of social norms for Northeast census region	0.01095
δ_m	Strength of social norms for Midwest census region	0.03052
δ_s	Strength of social norms for South census region	0.01900
δ_w	Strength of social norms for West census region	0.01313

Table A.6: Climate mitigation policy scenarios included in this study.

Year	Mitigation Policy
2050	REF
2050	$3.7\text{ W}/m^2$
2100	REF
2100	$3.7\text{ W}/m^2$

Table A.7: Population projection from base year 2005. Factors based on long term trends of United Nations Data, with details provided in Paltsev et al. (2015) [8].

Year	Value
2050	1.48
2100	1.73

Table A.8: Economic projection factors (GDP per capita). Data based on results from Paltsev et al. (2015). [\[8\]](#).

Year	REF	P3.7
2050	2.01	1.82
2100	3.94	3.37

Table A.9: Baseline mortality projection factors for ozone and PM_{2.5} Data based on results from West et al. (2013) [9].

Pollutant	Year	Value
Ozone	2050	1.24
	2100	1.64
PM _{2.5}	2050	1.12
	2100	0.92

Table A.10: Changes in population weighted national mean attributes compared to start-of-century. The values in this table are the difference in national population weighted exposure data and adaptation benefits and costs between future time periods and the reference period for the year 2000.

Scenario	Exposure without Adap- tation ($\mu g/m^3$)	Exposure under Rational Adap- tation ($\mu g/m^3$)	Adaptation Days Per Year	Exposure Reduc- tion per Adapta- tion Day ($\mu g/m^3$)	Adaptation Benefits (Trillion USD 2020)	Adaptation Costs (Trillion USD 2020)	Adaptation Net Ben- efits (Trillion USD 2020)
REF 2050	0.554	-0.062	27	-0.003	0.516	0.330	0.186
P37 2050	0.278	-0.164	25	-0.004	0.472	0.307	0.166
REF 2100	1.472	0.416	19	0.001	0.968	0.609	0.359
P37 2100	0.260	-0.053	12	-0.001	0.651	0.426	0.225

Table A.11: Effect of optimal adaptation on health effects of policy. The “Mitigate” scenarios are the costs and benefits accrued by enacting climate change mitigation policy and not considering PM_{2.5} adaptation. The “Rational Adapt” cases look at how including rational adaptation in the analysis reduces the cost (by reducing adaptation days from REF to P3.7) and reduces the benefits (because adaptation reduces the PM_{2.5} health burden). Policy benefits are reduced more than policy costs, leading to smaller benefit / cost ratios.

Case		Costs (Trillion USD 2020)	Costs Per Capita (USD 2020)	Benefits in POL Econ (Trillion USD 2020)	Benefits Per Capita (USD 2020)	% of costs offset (B/C ratio)	% change from Base of B/C ra- tio
Mitigate 2050	P3.7	5.042	18,800	0.295	1,100	6%	N/A
Rational P3.7 2050	Adapt	5.019	18,700	0.252	940	5%	-14%
Mitigate 2100	P3.7	17.042	54,400	2.304	7,400	14%	N/A
Rational P3.7 2100	Adapt	16.860	53,900	1.987	6,300	12%	-13%

Table A.12: PM_{2.5}-driven AQI alert days per year if threshold for alerts is > 150 compared to the number of rational adaptation days.

Scenario	Mean AQI Alert Days (Min, Max)	Rational Adaptation Days (Min, Max)
REF 2000	1 (0, 2)	7 (6, 9)
REF 2050	5 (4, 6)	34 (30, 37)
P37 2050	4 (3, 6)	32 (29, 35)
REF 2100	7 (5, 9)	26 (22, 30)
P37 2100	4 (3, 6)	19 (16, 21)

Appendix B

Supplemental Information for “Future Ozone and PM_{2.5} in the US Under Varying Climate Policy: Air Quality Alerts, Health Impacts, and Adaptation Implications”

B.1 Figures

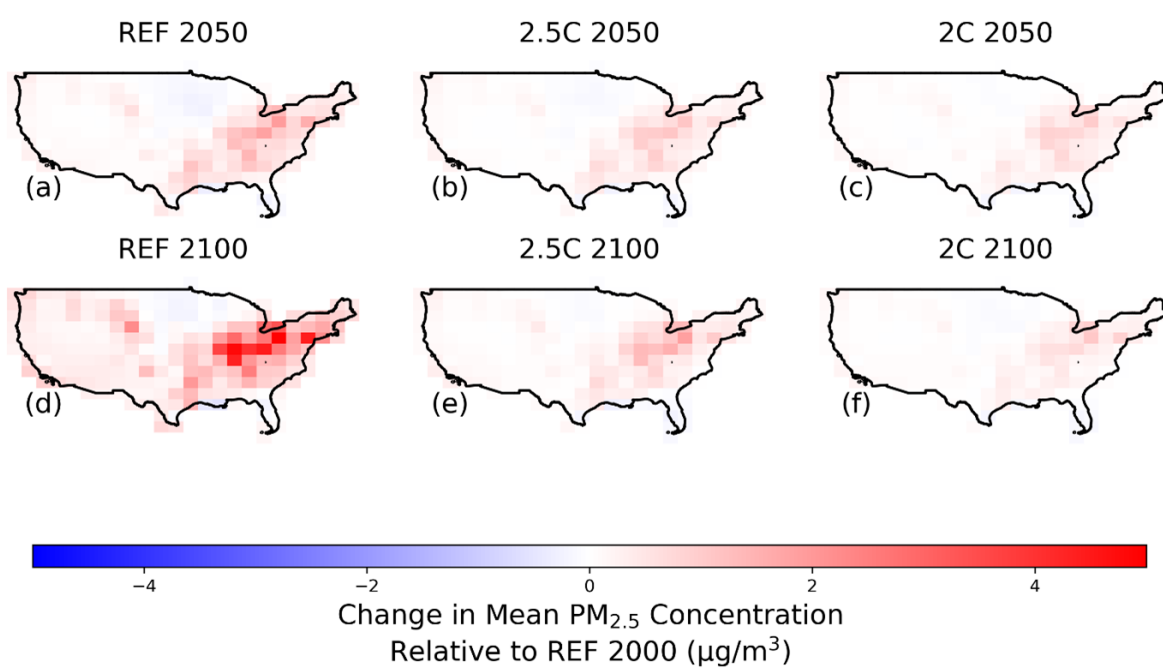


Figure B.1: Change in mean $PM_{2.5}$ concentration (g/m^3) for each grid cell in each counterfactual relative to REF 2000.

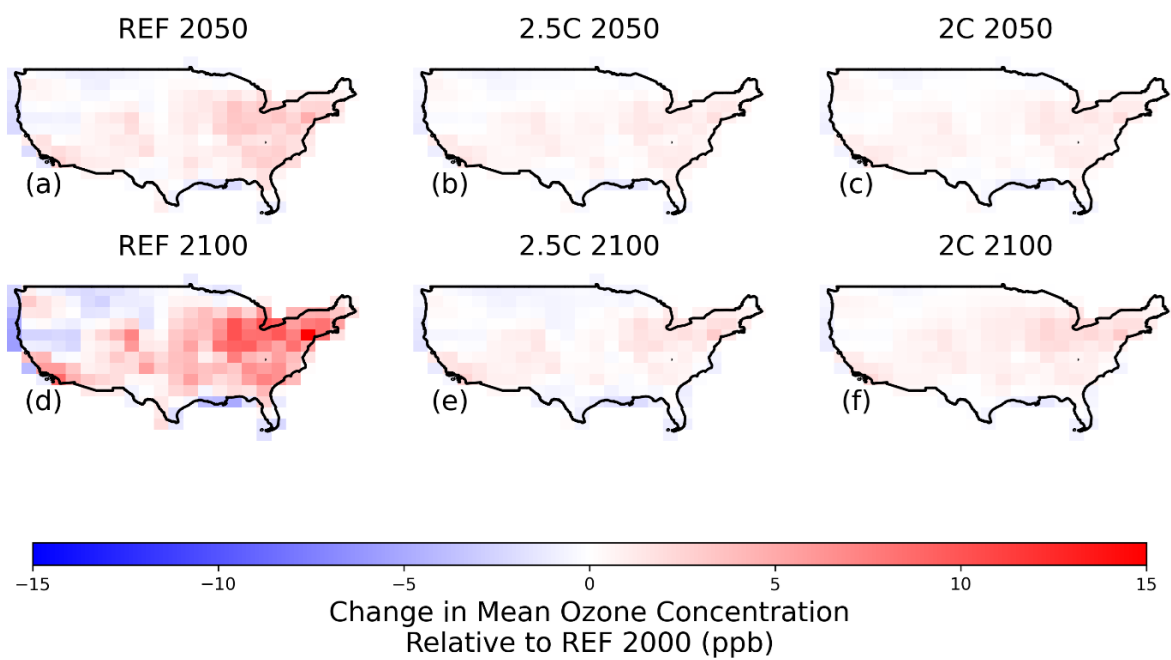


Figure B.2: Change in mean ozone concentration (ppb) for each grid cell in each counterfactual relative to REF 2000.

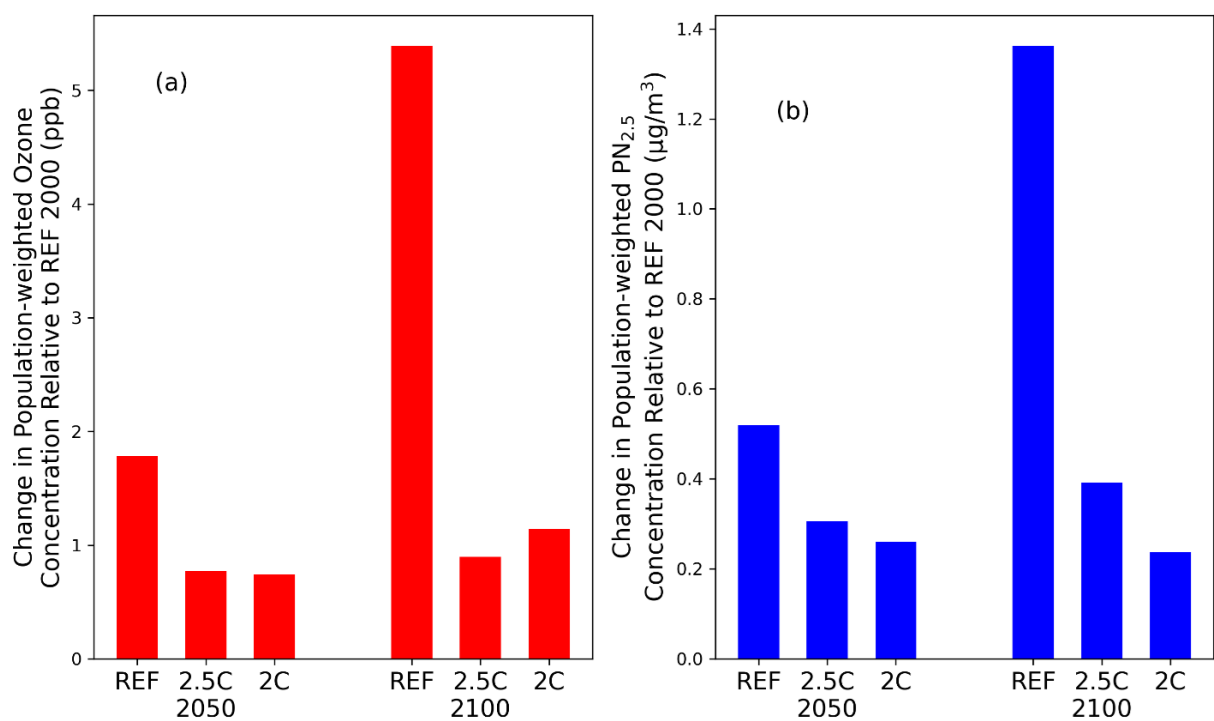


Figure B.3: Change in population-weighted mean ozone concentration (ppb) relative to REF 2000 (a). Change in population-weighted mean PM_{2.5} concentration (μg/m³) relative to REF 2000 (b).

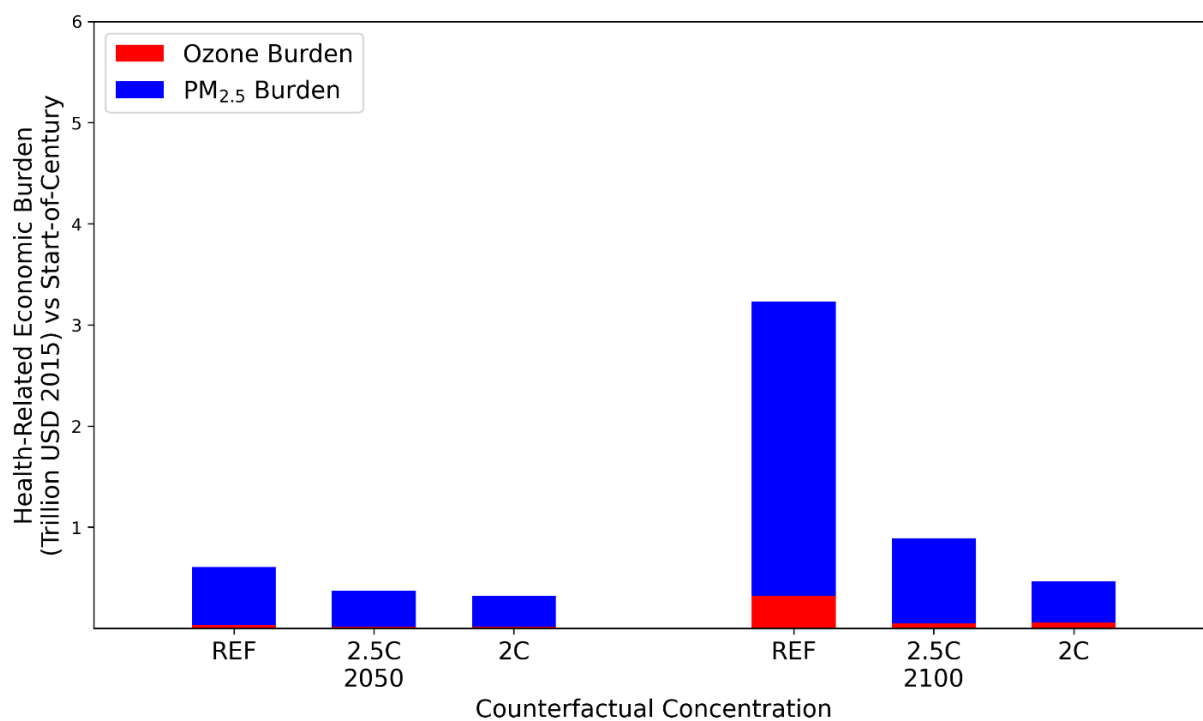


Figure B.4: Additional health-related economic burden for each counterfactual relative to REF 2000, broken down by source pollutant, adjusted for modeled future economic and population changes.

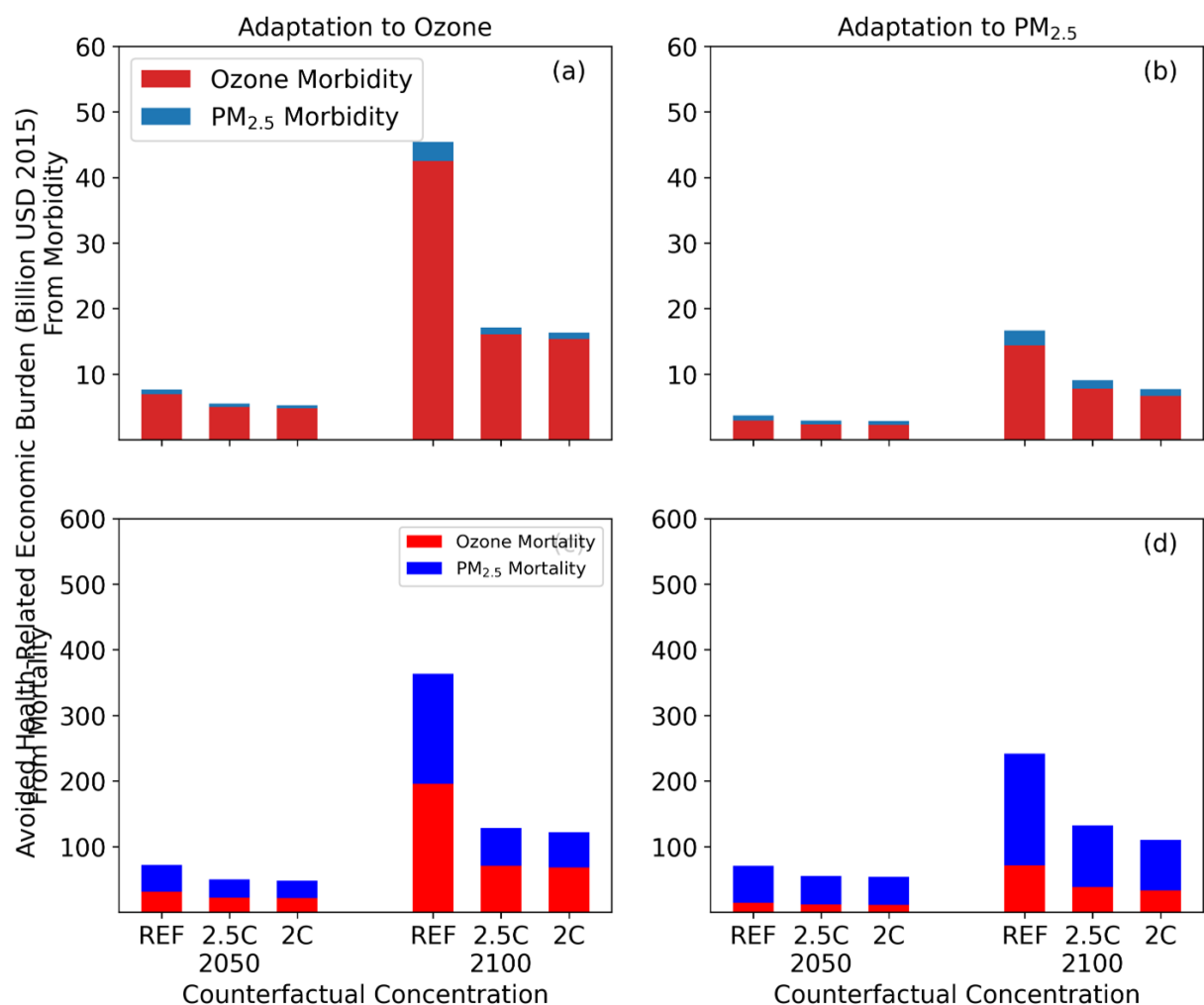


Figure B.5: Benefits of avoidance adaptation under different counterfactual concentrations (billions of 2015 USD). The avoided health burden, or health benefit, is gained by switching outdoor time to residential time during air quality alerts that apply to the full population (AQI $\geq$ 150, “Unhealthy”). Benefits are shown by the contribution of reducing exposure to ozone (red) and PM_{2.5} (blue), respectively. Adaptation to alerts triggered by high ozone levels is shown in (a) and (c). Adaptation to PM_{2.5}-driven alerts is shown in (b) and (d). Adaptation benefits from avoided morbidity are shown in (a) and (b) and adaptation benefits from avoided mortality are shown in (c) and (d). Values in this figure are adjusted for modeled future economic and population changes.

Table B.1: AQI thresholds and recommended adaptation behavior for ozone and PM_{2.5}. Adapted from the U.S. EPA AQI Technical Assistance Document [6].

AQI Category (Index Values)	8-hour Ozone Concentration (ppb)	Ozone Recommendation	24-hour PM _{2.5} Concentration (µg/m ³)	PM _{2.5} Recommendation
Good (Up to 50)	0-54	None.	0-12	None.
Moderate (51-100)	55-70	Unusually sensitive people should consider reducing prolonged or heavy outdoor exertion.	12.1-35.4	Unusually sensitive people should consider reducing prolonged or heavy exertion.
Unhealthy for Sensitive Groups (101-150)	71-85	People with lung disease (such as asthma), children, older adults, people who are active outdoors (including outdoor workers), people with certain genetic variants, and people with diets limited in certain nutrients should reduce prolonged or heavy outdoor exertion.	35.5-55.4	People with heart or lung disease, older adults, children, and people of lower socioeconomic status should reduce prolonged or heavy exertion.

Unhealthy (151-200)	86-105	People with lung disease (such as asthma), children, older adults, people who are active outdoors (including outdoor workers), people with certain genetic variants, and people with diets limited in certain nutrients should avoid prolonged or heavy outdoor exertion; everyone else should reduce prolonged or heavy outdoor exertion.	55.5-150.4	People with heart or lung disease, older adults, children, and people of lower socioeconomic status should avoid prolonged or heavy exertion; everyone else should reduce prolonged or heavy exertion.
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Very Unhealthy (201-300)	106-200	People with lung disease (such as asthma), children, older adults, people who are active outdoors (including outdoor workers), people with certain genetic variants, and people with diets limited in certain nutrients should avoid all outdoor exertion; everyone else should reduce outdoor exertion.	150.5-250.4	People with heart or lung disease, older adults, children, and people of lower socioeconomic status should avoid all physical activity outdoors. Everyone else should avoid prolonged or heavy exertion.
Hazardous (301-500)	N/A. Only 1 hour concentration.	Everyone should avoid all outdoor exertion.	250.5-500.4	Everyone should avoid all physical activity outdoors; people with heart or lung disease, older adults, children, and people of lower socioeconomic status should remain indoors and keep activity levels low.

Table B.2: Health endpoints considered for this study along with the responsible pollutant, affected age group, the epidemiological study it is based on, and the method by which it is valued.

Endpoint/Endpoint Group	Pollutant	Ages (years)	Epidemiological Studies	Valuation Method
Acute Myocardial Infarction (Nonfatal)	PM2.5	65-99	Wei et al. (2019)	Cost of illness based on medical costs and lost wages (Russell, 1998).
Minor Restricted Activity Days	Ozone, PM2.5	18-64	Ostro and Roth-schild (1989)	Median Willingness-to-pay estimate to avoid three-symptom combination based on Tolley et al. (1986).
Asthma Symptoms	Ozone	5-12	Lewis et al. (2013)	Based on parents' willingness-to-pay to relieve asthma symptoms in children and adults (Dickie and Messman, 2004).
Albuterol Use	PM2.5	6-17	Rabinovitch et al. (2006)	Based on the cost of the inhaler divided by the number of uses per inhaler.

Emergency Room Visits (Cardiovascular)	PM2.5	0-99	Ostro et al. (2016)	Estimates based on Healthcare Cost and Utilization Project (HCUP) matching ICD-10 codes to study results.
Emergency Room Visits (Respiratory)	Ozone, PM2.5	0-99	Barry et al. (2018) Krall et al. (2016)	Estimates based on HCUP matching ICD-10 codes to study results.
Hospital Admission (Cardiovascular)	PM2.5	65-99	Bell et al. (2015)	Cost of illness based on data reported by the Agency for Healthcare Research and Quality's Healthcare Utilization Project National Inpatient Sample (NIS) database (2016).
Hospital Admissions (Neurological)	PM2.5	65-99	Kioumourtoglou et al. (2016)	Lifetime cost of disease for Alzheimers (Alzheimer's Association (2020) and Jutkowitz et al. (2017) and Parkinson's (Yang et al. (2020))).

Hospital Admissions (Respiratory)	Ozone, PM2.5	65-99, 0-18, 65-99	Katsouyanni et al. (2009) Ostro et al. (2009) Bell et al. (2015)	Cost of illness based on data reported by the Agency for Healthcare Research and Quality's Healthcare Utilization Project NIS database (2016).
Stroke	PM2.5	65-99	Kloog et al. (2012)	Calculated based on the direct costs of hospitalization and the 360 days following hospital discharge (Mu et al., 2017).
Cardiac Arrest (Out of Hospital)	PM2.5	0-99, 18-99	Silverman et al. (2010) Rosenthal et al. (2008)	Estimated three-year medical costs associated with events based on administrative claims data (O'Sullivan et al., 2011).
Lung Cancer	PM2.5	30-99	Ensor et al. (2013) Gharibvand et al. (2016)	Derived from the medical costs associated with lung cancer treatment (Kaye et al., 2018).

Asthma		Ozone, PM2.5	0-17	Tetreault et al. (2016)	Lifetime costs of asthma including healthcare and lost productivity costs reported by Belova et al. (2020).
Hay Fever/Rhinitis		Ozone, PM2.5	3-17	Parker et al. (2009)	Cost of illness based on mean annual medical costs for patients with hay fever (Soni, 2008).
Mortality Cause)	(All	Ozone, PM2.5	0-99, 18-99	Katsouyanni et al. (2009) Pope et al. (2019)	Weibull distribution based on 26 Value of Statistical Life estimates from peer reviewed literature.
School Days	Loss	Ozone	5-17	Gilliland et al. (2001)	Based on lost wages given the probability that a parent stays home with the child.
Work Loss Days		PM2.5	18-64	Ostro (1987)	Median daily wage, county-specific

Table B.3: Infiltration factor F_{INF} values for each of the four microenvironments included in this study as well as the source of the data.

Microenvironment	Representative $\text{PM}_{2.5}$ Value	F_{INF}	Source
Residential	0.45		National average using National Renewable Energy Laboratory (NREL) ResStock [178] ACH values.
Commercial	0.35		Lower range of 0.35 and 0.49 used in Fisk and Chan (2017) [108] and Azimi and Stephens (2020) [144], respectively.
Vehicle	0.6		Fisk and Chan (2017)[108], based on Rodes et al. (1998) [226] and similar to 0.61 for outdoor ventilation mode driving in Hudda and Fruin (2013) [240].
Outdoors	1		

Table B.4: 95% CI of unadjusted health-related economic burden when comparing each counterfactual to REF 2000.

Counterfactual	95% Confidence Interval of Unadjusted Health-Related Economic Burden vs REF 2000 (Billion USD 2015)
REF 2050	(1.07, 617)
2.5C 2050	(-4.08, 410)
2C 2050	(-6.16, 356)
REF 2100	(29.7, 1634)
2.5C 2100	(-3.6, 499)
2C 2100	(-8.02, 285)

Table B.5: 95% CI of unadjusted health-related economic adaptation benefit under each counterfactual.

Counterfactual	95% Confidence Interval of Unadjusted Health-Related Economic Adaptation Benefit (Billion USD 2015)
REF 2000	(2.04, 50.8)
REF 2050	(5.64, 145)
2.5C 2050	(4.50, 116)
2C 2050	(4.47, 115)
REF 2100	(10.6, 274)
2.5C 2100	(4.89, 126)
2C 2100	(4.79, 123)

Appendix C

Supplemental Information for “Population Exposure to Outdoor Particulate Matter: Role of Buildings, Behavior, Ambient Air Quality, and the COVID-19 Pandemic”

C.1 Alternative Para-pandemic Periods

The COVID-19 pandemic affected time use most strongly during the initial lockdown periods at the onset of the pandemic in the US. Unfortunately, ATUS paused data collection from mid-March to early-May 2020. There is a clear increase in residential time from March to May 2020, and the value remains high throughout the year. In 2021, the fraction of time spent at home steadily decreases. In 2022, it levels off, with seasonal variation similar to 2019.

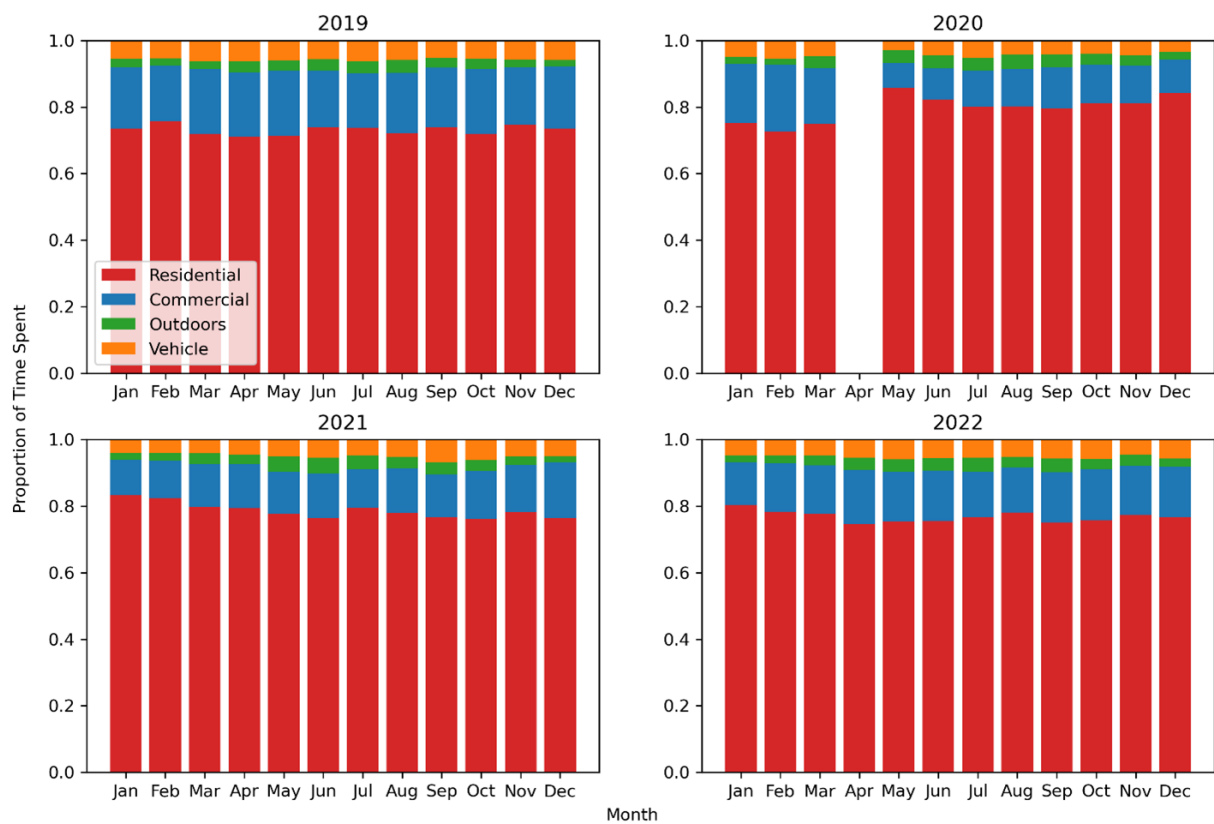


Figure C.1: Average time spent in each microenvironment across ATUS respondents for the years 2019-2022. Note that no data was collected during April 2020.

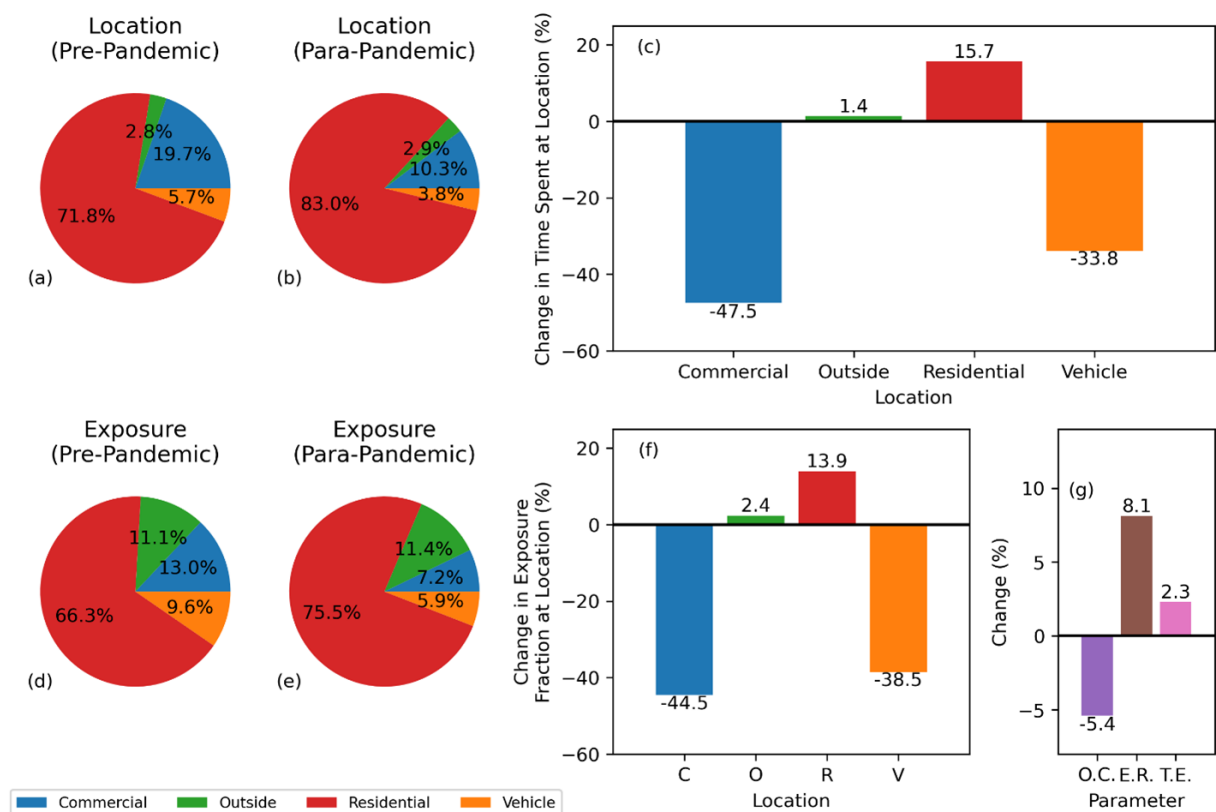


Figure C.2: Time use and exposure changes based on para-pandemic period of May 2020 – April 2021. Average proportion of time spent in each microenvironment pre-pandemic (a), post-pandemic onset (b), with the corresponding % change in time spent in each microenvironment after the pandemic onset (c). Also includes exposure by microenvironment under pre-pandemic time use patterns (d). Exposure by microenvironment under para-pandemic time use patterns, but without accounting for the population wearing masks (e). Corresponding % change in exposure from each microenvironment after the pandemic onset (f). (g) shows outdoor concentration (O.C.), activity-driven exposure ratio (E.R.), and total exposure (T.E.) changes of the para-pandemic period relative to the pre-pandemic period.

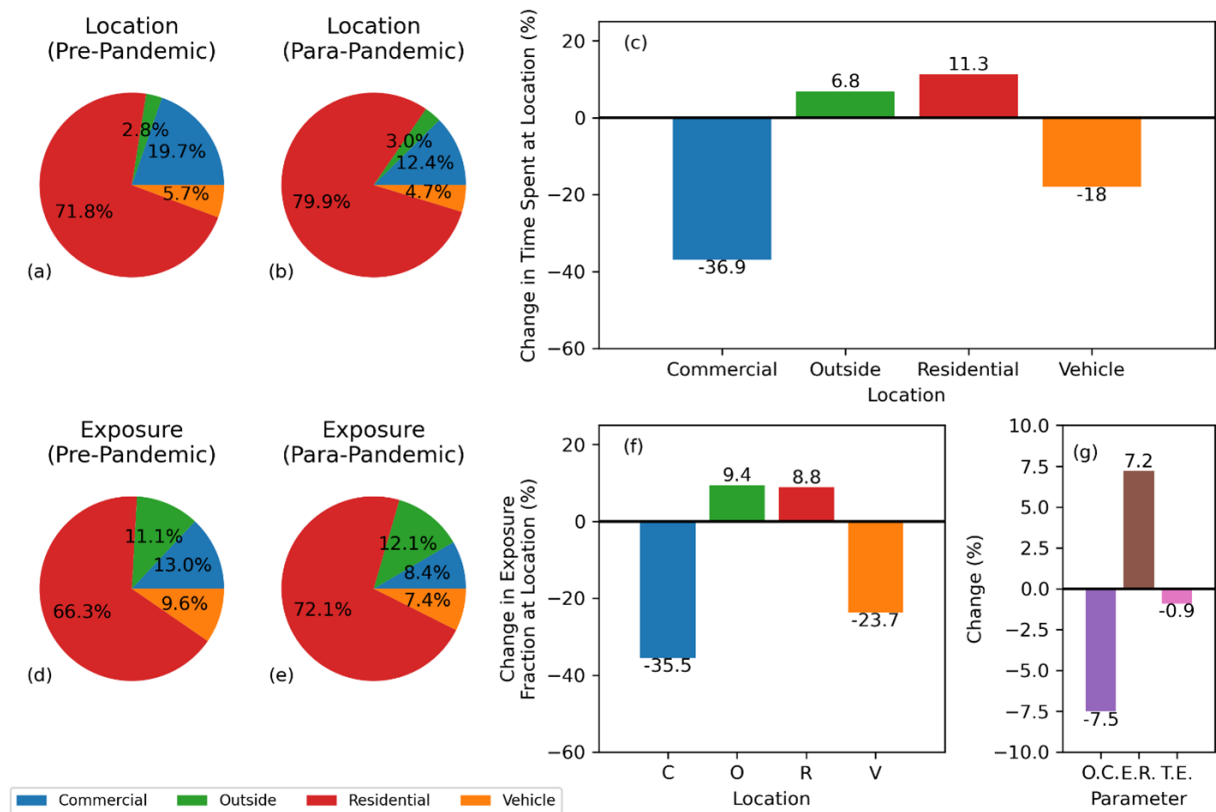


Figure C.3: Time use and exposure changes based on para-pandemic period of May 2020 – December 2022. Average proportion of time spent in each microenvironment pre-pandemic (a), post-pandemic onset (b), with the corresponding % change in time spent in each microenvironment after the pandemic onset (c). Also includes exposure by microenvironment under pre-pandemic time use patterns (d). Exposure by microenvironment under para-pandemic time use patterns, but without accounting for the population wearing masks (e). Corresponding % change in exposure from each microenvironment after the pandemic onset (f). (g) shows outdoor concentration (O.C.), activity-driven exposure ratio (E.R.), and total exposure (T.E.) changes of the para-pandemic period relative to the pre-pandemic period.

C.2 Daily vs Hourly Data for Analysis

This study uses daily pollution data for all the analysis. Daily data was used because it allows many more ATUS respondents to be included in the analysis at a minimal cost. While each ATUS respondent reports their activity data to the minute, high resolution PM_{2.5} concentration data is much rarer. The US EPA has much fewer PM_{2.5} monitors that measure at an hourly average frequency than daily average. Our analysis, Figure S4 shows that, on average, exposure calculated using hourly concentration data is within 10% of exposure calculated using daily concentration data. The hourly concentration data yield higher exposures because they capture the fact that people tend to be in higher FINE environments when outdoor pollution levels are highest.

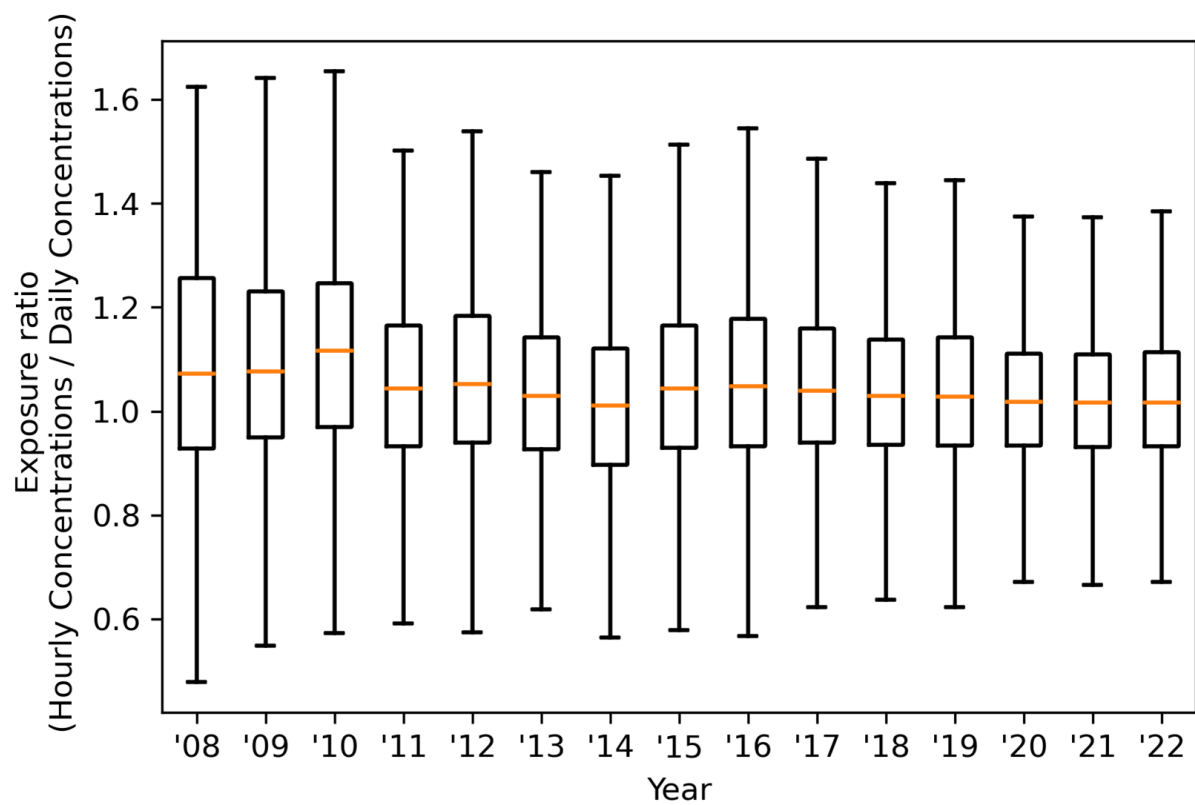


Figure C.4: Ratio of calculated exposure using hourly PM_{2.5} concentrations to exposure calculated using daily PM_{2.5} concentrations.

C.3 Variability in Parameter Data

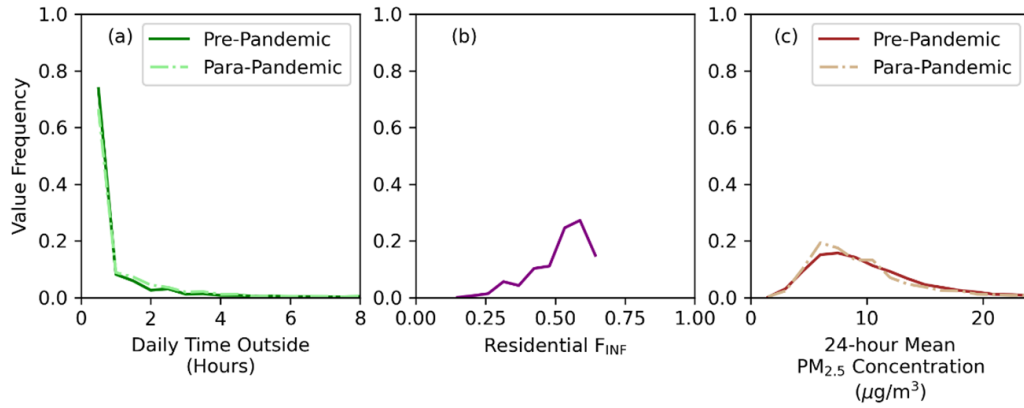


Figure C.5: Histograms of ATUS respondent data. Includes time spent outdoors (a), the calculated Residential microenvironment F_{INF} (b), and the local outdoor 24-hour mean $PM_{2.5}$ concentration on the ATUS activity day (c).

C.4 Alternative Parameters

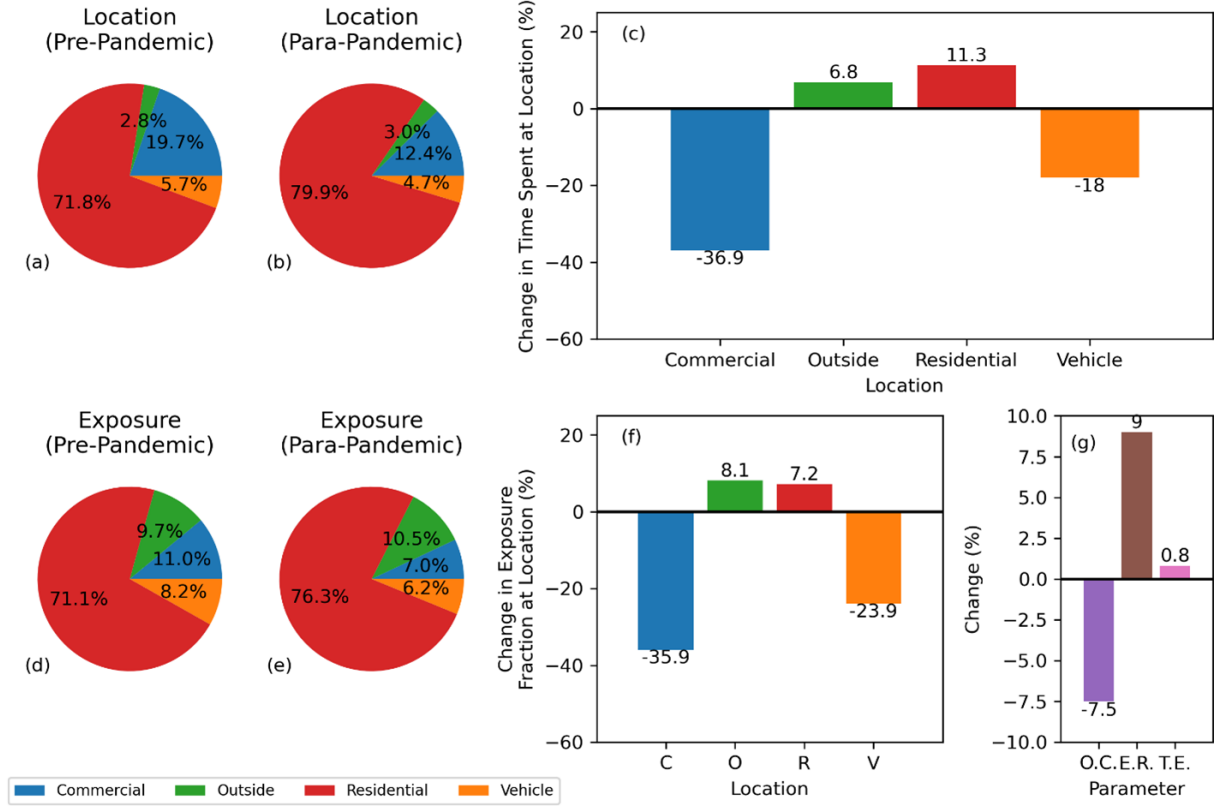


Figure C.6: Time use and exposure changes based on para-pandemic period of May 2020 – December 2020 and the penetration factor for $PM_{2.5}$ is 0.97. Average proportion of time spent in each microenvironment pre-pandemic (a), post-pandemic onset (b), with the corresponding % change in time spent in each microenvironment after the pandemic onset (c). Also includes exposure by microenvironment under pre-pandemic time use patterns (d). Exposure by microenvironment under para-pandemic time use patterns, but without accounting for the population wearing masks (e). Corresponding % change in exposure from each microenvironment after the pandemic onset (f). (g) shows outdoor concentration (O.C.), activity-driven exposure ratio (E.R.), and total exposure (T.E.) changes of the para-pandemic period relative to the pre-pandemic period.

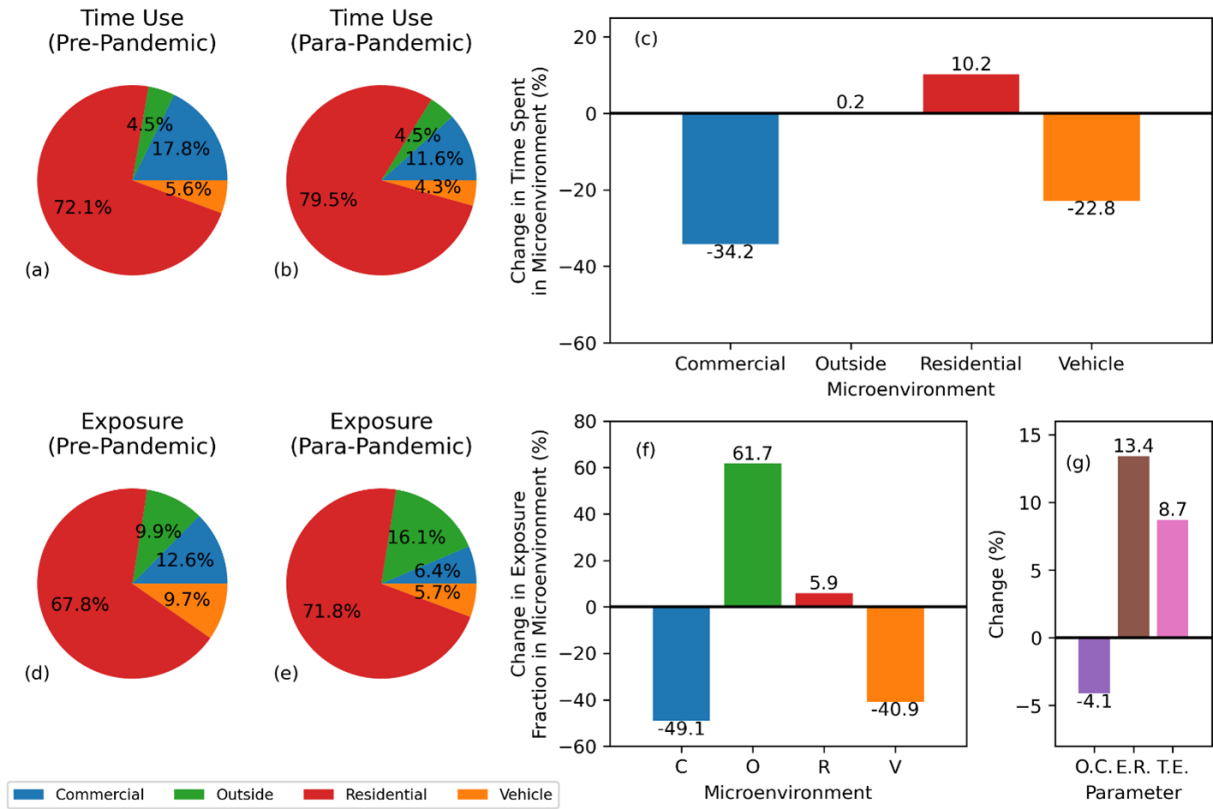


Figure C.7: Time use and exposure changes based on para-pandemic period of May 2020 – December 2020 with location and exposure data if Unknown locations are set to Outside. Average proportion of time spent in each microenvironment pre-pandemic (a), post-pandemic onset (b), with the corresponding % change in time spent in each microenvironment after the pandemic onset (c). Also includes exposure by microenvironment under pre-pandemic time use patterns (d). Exposure by microenvironment under para-pandemic time use patterns, but without accounting for the population wearing masks (e). Corresponding % change in exposure from each microenvironment after the pandemic onset (f). (g) shows outdoor concentration (O.C.), activity-driven exposure ratio (E.R.), and total exposure (T.E.) changes of the para-pandemic period relative to the pre-pandemic period.

C.5 Effect of Occupation on Exposure

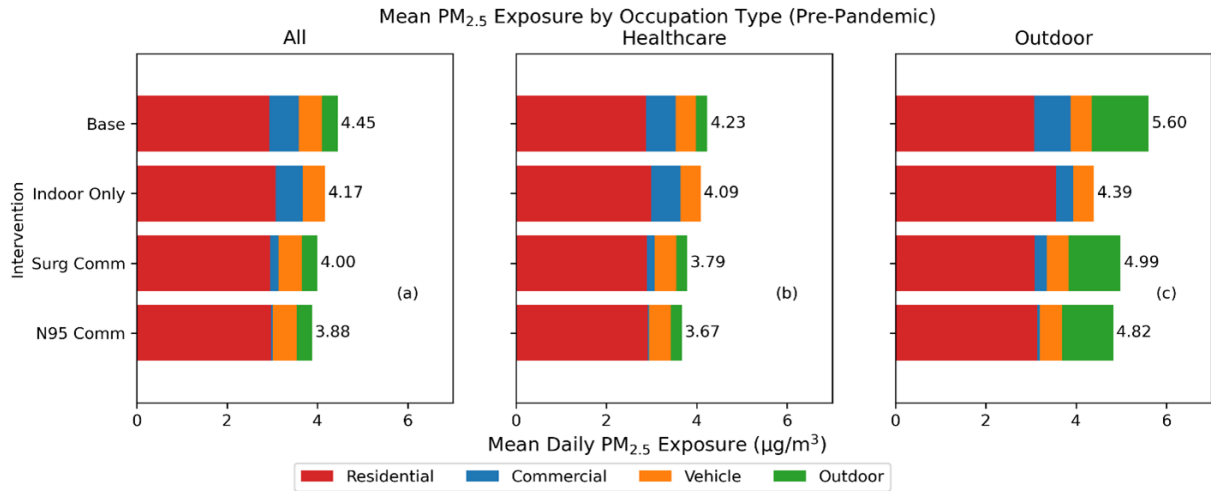


Figure C.8: Mean daily PM_{2.5} exposure before the pandemic under different adaptation scenarios. Includes contribution from each microenvironment. Subplots represent entire population (a), those who report having a job in healthcare (b), and those who work outdoors (c).

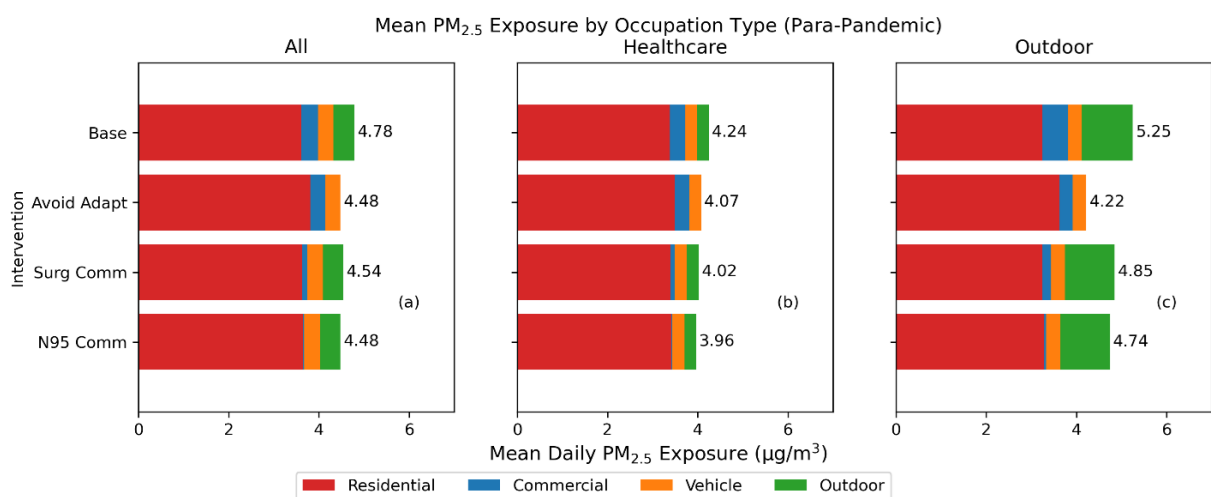


Figure C.9: Mean daily PM_{2.5} exposure during the pandemic under different adaptation scenarios. Includes contribution from each microenvironment. Subplots represent entire population (a), those who report having a job in healthcare (b), and those who work outdoors (c).

C.6 Tables

Table C.1: ATUS variables used in this study.

Variable	Description
TUCASEID	ATUS Case ID (14-digit identifier)
TUACTIVITY_N	Activity line number
TEWHERE	Edited: where were you during the activity?
TUACTDUR24	Duration of activity in minutes (last activity truncated at 4:00 a.m.)
TUSTARTTIM	Activity start time
TUSTOPTIME	Activity stop time
TRCODEP	Activity code (multi-year data files)
GTCBSA	Specific metropolitan core based statistical area (CBSA) code
TUDIARYDATE	Date of diary day (date about which the respondent was interviewed)
PRDTOCC1	Detailed occupation recode (main job)
TUFNWGTP	Statistical weight (multi-year data files)

Table C.2: Occupation codes gathered in ATUS/CPS and their descriptions, occupational F_{INF} values, and MET values.

PRDTOCC1 Code	Description	FINF	MET	Category
1	Management	0.35	1.73	Professional
2	Business and financial operations	0.35	1.67	Professional
3	Computer and mathematical science	0.35	1.58	Professional
4	Architecture and engineering	0.35	1.64	Professional
5	Life, physical, and social science	0.35	2.03	Professional
6	Community and social service	0.35	2.08	Service
7	Legal	0.35	1.5	Professional
8	Education instruction and library	0.35	2.5	Professional
9	Arts, design, entertainment, sports, media	0.35	2.13	Professional
10	Healthcare practitioner and technical	0.35	2.22	Professional
11	Healthcare support	0.35	2.83	Service
12	Protective service	0.6	2.56	Service
13	Food preparation and serving	0.35	2.58	Service
14	Building and grounds cleaning and maintenance	1	3.58	Outdoors
15	Personal care and service	0.35	2.53	Service
16	Sales and related	0.35	2	Professional
17	Office and administrative support	0.35	1.83	Service
18	Farming, fishing, forestry	1	3.67	Outdoors
19	Construction and extraction	1	4.29	Outdoors
20	Installation, maintenance, and repair	0.35	3.19	Service
21	Production	0.35	2.69	Service
22	Transportation and material moving	0.6	2.68	Service

Table C.3: Location codes gathered during ATUS/CPS and their corresponding description.

Location Code	Description
1	Respondent's home or yard
2	Respondent's workplace
3	Someone else's home
4	Restaurant or bar
5	Place of worship
6	Grocery store
7	Other store/mall
8	School
9	Outdoors away from home
10	Library
11	Other place
12	Car, truck, or motorcycle (driver)
13	Car, truck, or motorcycle (pass.)
14	Walking
15	Bus
16	Subway/train
17	Bicycle
18	Boat/ferry
19	Taxi/limousine service
20	Airplane
21	Other mode of transportation
30	Bank
31	Gym/health club
32	Post office
89	Unspecified place
99	Unspecified mode of transportation

Table C.4: ATUS activity codes with description, indoor-outdoor classification, and corresponding MET value.

	ATUS Activity Description	Class	MET
Code			
10101	Sleeping	Indoor	0.92
10102	Sleeplessness	Indoor	1
10199	Sleeping, n.e.c.	Indoor	0.94
10201	Washing, dressing and grooming oneself	Indoor	2.1
10299	Grooming, n.e.c.	Indoor	2.1
10301	Health-related self care	Indoor	1.29
10399	Self care, n.e.c.	Indoor	1.29
10401	Personal/Private activities	Indoor	1.04
10499	Personal activities, n.e.c.	Indoor	1.04
10501	Personal emergencies	Indoor	1.52
10599	Personal care emergencies, n.e.c.	Indoor	1.52
19999	Personal care, n.e.c.	Indoor	1.29
20101	Interior cleaning	Indoor	3.01
20102	Laundry	Indoor	2.07
20103	Sewing, repairing, & maintaining textiles	Indoor	1.5
20104	Storing interior hh items, inc. food	Indoor	3.39
20199	Housework, n.e.c.	Indoor	2.51
20201	Food and drink preparation	Indoor	2.16
20202	Food presentation	Indoor	2.38
20203	Kitchen and food clean-up	Indoor	2.54
20299	Food & drink prep, presentation, & clean-up, n.e.c.	Indoor	2.32
20301	Interior arrangement, decoration, & repairs	Indoor	3.33
20302	Building and repairing furniture	Indoor	4.25
20303	Heating and cooling	Indoor	4.42
20399	Interior maintenance, repair, & decoration, n.e.c.	Indoor	3.85
20401	Exterior cleaning	Outdoor	3.93
20402	Exterior repair, improvements, & decoration	Outdoor	4.75
20499	Exterior maintenance, repair & decoration, n.e.c.	Outdoor	4.49
20501	Lawn, garden, and houseplant care	Outdoor	3.66

20502	Ponds, pools, and hot tubs	Outdoor	2.64
20599	Lawn and garden, n.e.c.	Outdoor	3.45
20601	Care for animals and pets (not veterinary care)	Indoor	2.72
20602	Walking/Exercising/Playing with animals	Outdoor	3.8
20681	Care for animals and pets (not veterinary care)	Indoor	2.72
20699	Pet and animal care, n.e.c.	Indoor	2.72
20701	Vehicle repair and maintenance (by self)	Outdoor	2.93
20799	Vehicles, n.e.c.	Outdoor	2.93
20801	Appliance, tool, and toy set-up, repair, & maintenance (by self)	Indoor	2.98
20899	Appliances and tools, n.e.c.	Indoor	2.98
20901	Financial management	Indoor	1.8
20902	Household & personal organization and planning	Indoor	2.11
20903	HH & personal mail & messages (except e-mail)	Indoor	1.9
20904	HH & personal e-mail and messages	Indoor	1.8
20905	Home security	Indoor	2.88
20999	Household management, n.e.c.	Indoor	2.13
29999	Household activities, n.e.c.	Indoor	2.93
30101	Physical care for hh children	Indoor	2.67
30102	Reading to/with hh children	Indoor	1.3
30103	Playing with hh children, not sports	Indoor	3.26
30104	Arts and crafts with hh children	Indoor	1.5
30105	Playing sports with hh children	Outdoor	5
30186	Talking with/listening to hh children	Indoor	1.5
30108	Organization & planning for hh children	Indoor	1.81
30106	Talking with/listening to hh children	Indoor	1.5
30109	Looking after hh children (as a primary activity)	Indoor	1.71
30110	Attending hh children's events	Unknown	1.5
30111	Waiting for/with hh children	Unknown	1.3
30112	Picking up/dropping off hh children	Outdoor	2
30199	Caring for & helping hh children, n.e.c.	Indoor	2.21
30201	Homework (hh children)	Indoor	1.66

30202	Meetings and school conferences (hh children)	Indoor	1.53
30203	Home schooling of hh children	Indoor	1.5
30204	Waiting associated with hh children's education	Indoor	1.3
30299	Activities related to hh child's education, n.e.c.	Indoor	1.57
30301	Providing medical care to hh children	Indoor	2.5
30302	Obtaining medical care for hh children	Indoor	1.5
30303	Waiting associated with hh children's health	Indoor	1.3
30399	Activities related to hh child's health, n.e.c.	Indoor	2.03
30401	Physical care for hh adults	Indoor	2.89
30402	Looking after hh adult (as a primary activity)	Indoor	2
30403	Providing medical care to hh adult	Indoor	2.5
30404	Obtaining medical and care services for hh adult	Indoor	1.5
30405	Waiting associated with caring for household adults	Indoor	1.3
30499	Caring for household adults, n.e.c.	Indoor	2.16
30501	Helping hh adults	Indoor	2.05
30502	Organization & planning for hh adults	Indoor	1.68
30503	Picking up/dropping off hh adult	Outdoor	2
30504	Waiting associated with helping hh adults	Indoor	1.5
30599	Helping household adults, n.e.c.	Indoor	1.81
39999	Caring for & helping hh members, n.e.c.	Indoor	2.08
40101	Physical care for nonhh children	Indoor	2.72
40102	Reading to/with nonhh children	Indoor	1.3
40103	Playing with nonhh children, not sports	Indoor	3.3
40104	Arts and crafts with nonhh children	Indoor	1.5
40105	Playing sports with nonhh children	Outdoor	5
40106	Talking with/listening to nonhh children	Indoor	1.5
40186	Talking with/listening to nonhh children	Indoor	1.5
40108	Organization & planning for nonhh children	Indoor	1.84
40109	Looking after nonhh children (as primary activity)	Indoor	1.67
40110	Attending nonhh children's events	Unknown	1.5
40111	Waiting for/with nonhh children	Unknown	1.3

40112	Dropping off/picking up nonhh children	Outdoor	1
40199	Caring for and helping nonhh children, n.e.c.	Indoor	2.16
40201	Homework (nonhh children)	Indoor	1.66
40202	Meetings and school conferences (nonhh children)	Indoor	1.53
40203	Home schooling of nonhh children	Indoor	1.5
40204	Waiting associated with nonhh children's education	Indoor	1.3
40299	Activities related to nonhh child's educ., n.e.c.	Indoor	1.57
40301	Providing medical care to nonhh children	Indoor	2.5
40302	Obtaining medical care for nonhh children	Indoor	1.5
40303	Waiting associated with nonhh children's health	Indoor	1.3
40399	Activities related to nonhh child's health, n.e.c.	Indoor	2.03
40401	Physical care for nonhh adults	Indoor	2.89
40402	Looking after nonhh adult (as a primary activity)	Indoor	2
40403	Providing medical care to nonhh adult	Indoor	2.5
40404	Obtaining medical and care services for nonhh adult	Indoor	1.5
40405	Waiting associated with caring for nonhh adults	Indoor	1.3
40499	Caring for nonhh adults, n.e.c.	Indoor	2.16
40501	Housework, cooking, & shopping assistance for nonhh adults	Indoor	2.38
40502	House & lawn maint & repair assistance for nonhh adults	Outdoor	4.3
40503	Animal & pet care assistance for nonhh adults	Indoor	3
40504	Vehicle & appliance maint/repair assistance for nonhh adults	Unknown	3.33
40505	Financial management assistance for nonhh adults	Indoor	1.8
40506	Hh management & paperwork assistance for nonhh adults	Indoor	1.74
40507	Picking up/dropping off nonhh adult	Outdoor	2

40508	Waiting associated with helping nonhh adults	Indoor	1.5
40599	Helping nonhh adults, n.e.c.	Indoor	2.64
49999	Caring for & helping nonhh members, n.e.c.	Indoor	2.18
50101	Work, Main job	Unknown	1
50102	Work, Other jobs	Unknown	1
50103	Security procedures related to work	Indoor	2.33
50104	Waiting associated with working	Indoor	2
50189	Working, n.e.c.	Indoor	2.18
50199	Working, n.e.c.	Indoor	2.18
50201	Socializing, relazing, and leisure as part of job	Indoor	1.21
50202	Eating and drinking as part of job	Indoor	1.5
50203	Sports and exercise as part of job	Outdoor	5.1
50204	Security procedures as part of job	Indoor	2.33
50205	Waiting associated with work-related activities	Indoor	2
50289	Work-related activities, n.e.c.	Indoor	2.18
50299	Work-related activities, n.e.c.	Indoor	2.18
50301	Income-generating hobbies, crafts, and food	Indoor	2.15
50302	Income-generating performances	Indoor	2.5
50303	Income-generating services	Indoor	1.5
50304	Income-generating rental property activities	Indoor	1.5
50305	Waiting associated with other income-generating activities	Indoor	2
50389	Other income-generating activities, n.e.c.	Indoor	2.18
50399	Other income-generating activities, n.e.c.	Indoor	2.18
50401	Job search activities	Indoor	1.5
50403	Job interviewing	Indoor	2
50404	Waiting associated with job search or interview	Indoor	2
50405	Security procedures related to job search/interviewing	Indoor	2.33
50481	Job search and interviewing, n.e.c.	Indoor	2.18
50499	Job search and interviewing, n.e.c.	Indoor	2.18
59999	Work and work-related activities n.e.c.	Indoor	2.18
60101	Taking class for degree, certification, or licensure	Indoor	1.82

60102	Taking class for personal interest	Indoor	2.4
60103	Waiting associated with taking classes	Indoor	1.8
60104	Security procedures rel. to taking classes	Indoor	2.33
60199	Taking class, n.e.c.	Indoor	2.23
60201	Extracurricular club activities	Unknown	1.63
60202	Extracurricular music & performance activities	Indoor	2.5
60203	Extracurricular student government activities	Indoor	1.9
60299	Education-related extracurricular activities, n.e.c.	Indoor	1.84
60289	Education-related extracurricular activities, n.e.c.	Indoor	1.84
60301	Research/homework for class for degree, certification, or licensure	Indoor	1.8
60302	Research/homework for class for pers. interest	Indoor	1.8
60303	Waiting associated with research/homework	Indoor	1
60399	Research/homework n.e.c.	Indoor	1.75
60401	Administrative activities: class for degree, certification, or licensure	Indoor	1.9
60402	Administrative activities: class for personal interest	Indoor	2
60403	Waiting associated w/admin. activities (education)	Indoor	2
60499	Administrative for education, n.e.c.	Indoor	1.96
69999	Education, n.e.c.	Indoor	2.02
70101	Grocery shopping	Indoor	2.1
70102	Purchasing gas	Outdoor	2.1
70103	Purchasing food (not groceries)	Indoor	2.33
70104	Shopping, except groceries, food and gas	Indoor	2.21
70105	Waiting associated with shopping	Indoor	1.2
70199	Shopping, n.e.c.	Indoor	2.16
70201	Comparison shopping	Indoor	1.9
70299	Researching purchases, n.e.c.	Indoor	1.9
70301	Security procedures rel. to consumer purchases	Indoor	2.33

70399	Security procedures rel. to consumer purchases, n.e.c.	Indoor	2.33
79999	Consumer purchases, n.e.c.	Indoor	2.15
80101	Using paid childcare services	Indoor	1.91
80102	Waiting associated w/purchasing childcare svcs	Indoor	1.3
80199	Using paid childcare services, n.e.c.	Indoor	1.86
80201	Banking	Indoor	1.84
80202	Using other financial services	Indoor	1.53
80203	Waiting associated w/banking/financial services	Indoor	1.2
80299	Using financial services and banking, n.e.c.	Indoor	1.67
80301	Using legal services	Indoor	1.65
80302	Waiting associated with legal services	Indoor	1.3
80399	Using legal services, n.e.c.	Indoor	1.6
80401	Using health and care services outside the home	Indoor	1.5
80402	Using in-home health and care services	Indoor	1.5
80403	Waiting associated with medical services	Indoor	1.8
80499	Using medical services, n.e.c.	Indoor	1.53
80501	Using personal care services	Indoor	1.18
80502	Waiting associated w/personal care services	Indoor	1.3
80599	Using personal care services, n.e.c.	Indoor	1.19
80601	Activities rel. to purchasing/selling real estate	Indoor	2.02
80602	Waiting associated w/purchasing/selling real estate	Indoor	1.3
80699	Using real estate services, n.e.c.	Indoor	1.98
80701	Using veterinary services	Indoor	1.84
80702	Waiting associated with veterinary services	Indoor	1.3
80799	Using veterinary services, n.e.c.	Indoor	1.75
80801	Security procedures rel. to professional/personal svcs.	Indoor	2.33
80899	Security procedures rel. to professional/personal svcs n.e.c.	Indoor	2.33
89999	Professional and personal services, n.e.c.	Indoor	1.68
90101	Using interior cleaning services	Indoor	1.56
90102	Using meal preparation services	Indoor	1.62

90103	Using clothing repair and cleaning services	Indoor	2
90104	Waiting associated with using household services	Indoor	1.53
90199	Using household services, n.e.c.	Indoor	1.7
90201	Using home maint/repair/décor/construction svcs	Indoor	1.54
90202	Waiting associated w/ home main/repair/décor/constr	Indoor	1.65
90299	Using home maint/repair/décor/constr services, n.e.c.	Indoor	1.55
90301	Using pet services	Indoor	1.66
90302	Waiting associated with pet services	Indoor	1.77
90399	Using pet services, n.e.c.	Indoor	1.68
90401	Using lawn and garden services	Unknown	1.5
90402	Waiting associated with using lawn & garden services	Unknown	1.3
90499	Using lawn and garden services, n.e.c.	Unknown	1.47
90501	Using vehicle maintenance or repair services	Unknown	1.75
90502	Waiting associated with vehicle main. or repair svcs	Indoor	1.53
90599	Using vehicle maint. & repair svcs, n.e.c.	Unknown	1.68
99999	Using household services, n.e.c.	Unknown	1.61
100101	Using police and fire services	Unknown	1.72
100102	Using social services	Indoor	1.71
100103	Obtaining licenses & paying fines, fees, taxes	Indoor	1.87
100199	Using government services, n.e.c.	Indoor	1.78
100201	Civic obligations & participation	Indoor	1.65
100299	Civic obligations & participation, n.e.c.	Indoor	1.65
100304	Waiting associated with using government services	Indoor	2
100381	Waiting associated with using government services	Indoor	2
100383	Waiting associated w/civic obligations & participation	Indoor	2
100305	Waiting assoc. w/govt svcs or civic obligations, n.e.c.	Indoor	2
100399	Waiting assoc. w/govt svcs or civic obligations, n.e.c.	Indoor	2

100401	Security procedures rel. to govt svcs/civic obligations	Indoor	2.33
100499	Security procedures rel. to govt svcs/civic obligations, n.e.c.	Indoor	2.33
109999	Government services, n.e.c.	Indoor	1.78
110101	Eating and drinking	Indoor	1.5
110199	Eating and drinking, n.e.c.	Indoor	1.5
110201	Waiting associated w/eating & drinking	Indoor	2
110281	Waiting associated w/eating & drinking	Indoor	2
110289	Waiting associated with eating & drinking, n.e.c.	Indoor	1.67
110299	Waiting associated with eating & drinking, n.e.c.	Indoor	1.67
119999	Eating and drinking, n.e.c.	Indoor	1.83
120101	Socializing and communicating with others	Unknown	1.5
120199	Socializing and communicating, n.e.c.	Unknown	1.5
120201	Attending or hosting parties/receptions/ceremonies	Indoor	1.86
120202	Attending meetings for personal interest (not volunteering)	Indoor	1.5
120299	Attending/hosting social events, n.e.c.	Indoor	1.64
120301	Relaxing, thinking	Indoor	1.21
120302	Tobacco and drug use	Indoor	1.13
120303	Television and movies (not religious)	Indoor	1.33
120304	Television (religious)	Indoor	1
120305	Listening to the radio	Indoor	1.15
120306	Listening to/playing music (not radio)	Indoor	1.38
120307	Playing games	Indoor	1.5
120308	Computer use for leisure (exc. Games)	Indoor	1.9
120309	Arts and crafts as a hobby	Indoor	2.18
120310	Collecting as a hobby	Indoor	1.7
120311	Hobbies, except arts & crafts and collecting	Indoor	2.15
120312	Reading for personal interest	Indoor	1.6
120313	Writing for personal interest	Indoor	1.8
120399	Relaxing and leisure, n.e.c.	Indoor	1.54
120401	Attending performing arts	Indoor	1.5
120402	Attending museums	Indoor	2.1
120403	Attending movies/film	Indoor	2.1

120404	Attending gambling establishments	Indoor	2.3
120405	Security procedures rel. to arts & entertainment	Indoor	2.33
120499	Arts and entertainment, n.e.c.	Indoor	1.63
120501	Waiting assoc. w/socializing & communicating	Indoor	1.3
120502	Waiting assoc. w/attending/hosting social events	Indoor	1.3
120503	Waiting associated with relaxing/leisure	Indoor	1.3
120504	Waiting associated with arts & entertainment	Indoor	1.3
120599	Waiting associated with socializing, n.e.c.	Indoor	1.3
129999	Socializing, relaxing, and leisure, n.e.c.	Indoor	1.62
130101	Doing aerobics	Indoor	6.83
130102	Playing baseball	Outdoor	5
130103	Playing basketball	Unknown	8
130104	Biking	Outdoor	8
130105	Playing billiards	Indoor	2.5
130106	Boating	Outdoor	4.64
130107	Bowling	Indoor	3
130108	Climbing, spelunking, caving	Outdoor	9.5
130109	Dancing	Indoor	4.5
130110	Participating in equestrian sports	Outdoor	5.33
130111	Fencing	Indoor	6
130112	Fishing	Outdoor	4.5
130113	Playing football	Outdoor	8
130114	Golfing	Outdoor	3.75
130115	Doing gymnastics	Indoor	4
130116	Hiking	Outdoor	6
130117	Playing hockey	Indoor	8
130118	Hunting	Outdoor	4.5
130119	Participating in martial arts	Indoor	10
130120	Playing racquet sports	Indoor	8.5
130121	Participating in rodeo competitions	Outdoor	6
130122	Rollerblading	Outdoor	6
130123	Playing rugby	Outdoor	10
130124	Running	Outdoor	7.5
130125	Skiing, ice skating, snowboarding	Outdoor	7

130126	Playing soccer	Unknown	7
130127	Softball	Outdoor	5
130128	Using cardiovascular equipment	Indoor	8
130129	Vehicle touring/racing	Outdoor	3.3
130130	Playing volleyball	Unknown	5.5
130131	Walking	Outdoor	3.8
130132	Participating in water sports	Outdoor	5.22
130133	Weightlifting/strength training	Indoor	3
130134	Working out, unspecified	Unknown	2.5
130135	Wrestling	Indoor	6
130136	Doing yoga	Indoor	3
130199	Playing sports n.e.c.	Unknown	5.1
130201	Watching aerobics	Unknown	1.5
130202	Watching baseball	Unknown	1.5
130203	Watching basketball	Unknown	1.5
130204	Watching biking	Unknown	1.5
130205	Watching billiards	Indoor	1.5
130206	Watching boating	Outdoor	1.5
130207	Watching bowling	Indoor	1.5
130208	Watching climbing, spelunking, caving	Outdoor	1.5
130209	Watching dancing	Unknown	1.5
130210	Watching equestrian sports	Unknown	1.5
130211	Watching fencing	Indoor	1.5
130212	Watching fishing	Outdoor	1.5
130213	Watching football	Outdoor	1.5
130214	Watching golfing	Outdoor	1.5
130215	Watching gymnastics	Indoor	1.5
130216	Watching hockey	Indoor	1.5
130217	Watching martial arts	Indoor	1.5
130218	Watching racquet sports	Unknown	1.5
130219	Watching rodeo competitions	Unknown	1.5
130220	Watching rollerblading	Unknown	1.5
130221	Watching rugby	Unknown	1.5
130222	Watching running	Unknown	1.5
130223	Watching skiing, ice skating, snowboarding	Outdoor	1.5
130224	Watching soccer	Outdoor	1.5
130225	Watching softball	Outdoor	1.5
130226	Watching vehicle touring/racing	Outdoor	1.5

130227	Watching volleyball	Outdoor	1.5
130228	Watching walking	Outdoor	1.5
130229	Watching water sports	Outdoor	1.5
130230	Watching weightlifting/strength training	Indoor	1.5
130231	Watching people working out, unspecified	Unknown	1.5
130232	Watching wrestling	Indoor	1.5
130299	Attending sporting events, n.e.c.	Indoor	1.5
130301	Waiting related to playing sports or exercising	Unknown	1.5
130302	Waiting related to attending sporting events	Unknown	1.5
130399	Waiting associated with sports, exercise, & recreation, n.e.c.	Unknown	1.5
130401	Security related to playing sports or exercising	Indoor	2.33
130402	Security related to attending sporting events	Indoor	2.33
130499	Security related to sports, exercise, & recreation, n.e.c.	Indoor	2.33
139999	Sports, exercise, & recreation, n.e.c.	Indoor	4.78
140101	Attending religious services	Indoor	1.42
140102	Participation in religious practices	Indoor	1.89
140103	Waiting associated w/religious & spiritual activities	Indoor	1.5
140104	Security procedures rel. to religious & spiritual activities	Indoor	2.33
140105	Religious education activities	Indoor	2.2
149999	Religious and spiritual activities, n.e.c.	Indoor	1.75
150101	Computer use	Indoor	1.5
150102	Organizing and preparing	Indoor	1.5
150103	Reading	Indoor	1.5
150104	Telephone calls (except hotline counseling)	Indoor	1.5
150105	Writing	Indoor	1.5
150106	Fundraising	Indoor	1.7
150199	Administrative & support activities, n.e.c.	Indoor	1.55
150201	Food preparation, presentation, clean-up	Indoor	2.45
150202	Collecting & delivering clothing & other goods	Indoor	2.65
150203	Providing care	Indoor	2.25
150204	Teaching, leading, counseling, mentoring	Indoor	2.14

150299	Social service & care activities, n.e.c.	Indoor	1.97
150301	Building houses, wildlife sites, & other structures	Outdoor	4.5
150302	Indoor & outdoor maintenance, repair, & clean-up	Unknown	3.56
150399	Indoor & outdoor maint, building & clean-up activities, n.e.c.	Unknown	3.82
150401	Performing	Indoor	2.92
150402	Serving at volunteer events & cultural activities	Unknown	1.83
150499	Participating in performance & cultural activities, n.e.c.	Unknown	2.51
150501	Attending meetings, conferences, & training	Indoor	1.5
150589	Attending meetings, conferences, & training, n.e.c.	Indoor	1.5
150599	Attending meetings, conferences, & training, n.e.c.	Indoor	1.5
150601	Public health activities	Indoor	2
150602	Public safety activities	Indoor	2.5
150699	Public health & safety activities, n.e.c.	Indoor	2.25
150701	Waiting associated with volunteer activities	Indoor	2
159989	Volunteer activities, n.e.c.	Unknown	2.29
159999	Volunteer activities, n.e.c.	Unknown	2.29
160101	Telephone calls to/from family members	Indoor	1.5
160102	Telephone calls to/from friends, neighbors, or acquaintances	Indoor	1.5
160103	Telephone calls to/from education services providers	Indoor	1.5
160104	Telephone calls to/from salespeople	Indoor	1.5
160105	Telephone calls to/from professional or personal care svcs providers	Indoor	1.5
160106	Telephone calls to/from household services providers	Indoor	1.5
160107	Telephone calls to/from paid child or adult care providers	Indoor	1.5
160108	Telephone calls to/from government officials	Indoor	1.5
160199	Telephone calls (to or from) n.e.c	Indoor	1.5
160201	Waiting associated with telephone calls	Indoor	1.5

160299	Waiting associated with telephone calls, n.e.c.	Indoor	1.5
169999	Telephone calls, n.e.c.	Indoor	1.5
169989	Telephone calls, n.e.c.	Indoor	1.5
180101	Travel related to personal care	Vehicle	2
180199	Travel related to personal care, n.e.c.*	Vehicle	2
180201	Travel related to housework	Vehicle	2
180202	Travel related to food and drink prep, clean-up, presentation	Vehicle	2
180203	Travel related to interior maintenance, repair, and decoration	Vehicle	2
180204	Travel related to exterior maintenance, repair, and decoration	Vehicle	2
180205	Travel related to lawn, garden, and house-plant care	Vehicle	2
180206	Travel related to care for animals and pets (not vet care)	Vehicle	2
180207	Travel related to vehicle care and maintenance (by self)	Vehicle	2
180208	Travel related to appliance, tool, and toy set up, repair and maintenance (by self)	Vehicle	2
180209	Travel related to household management	Vehicle	2
180280	Travel related to household activities	Vehicle	2
180299	Travel related to household activities	Vehicle	2
180301	Travel related to caring for and helping hh children	Vehicle	2
180302	Travel related to hh children's education	Vehicle	2
180303	Travel related to hh children's health	Vehicle	2
180304	Travel related to caring for hh adults	Vehicle	2
180305	Travel related to helping hh adults	Vehicle	2
180381	Travel related to caring for and helping hh children	Vehicle	2
180382	Travel related to caring for and helping hh adults	Vehicle	2
180399	Travel rel. to caring for & helping hh members, n.e.c.*	Vehicle	2
180401	Travel related to	Vehicle	2

180402	Travel related to caring for and helping non hh children	Vehicle	2
180403	Travel related to non hh children's education	Vehicle	2
180404	Travel related to non hh children's health	Vehicle	2
180405	Travel related to caring for non hh adults	Vehicle	2
180481	Travel related to helping non hh adults	Vehicle	2
180482	Travel related to caring for and helping nonhh adults	Vehicle	2
180499	Travel rel. to caring for & helping nonhh members, n.e.c.*	Vehicle	2
180501	Travel related to working	Vehicle	2
180502	Travel related to work-related activities	Vehicle	2
180503	Travel related to income-generating activities	Vehicle	2
180504	Travel related to job searching and interviewing	Vehicle	2
180589	Travel related to work, n.e.c.*	Vehicle	2
180599	Travel related to work, n.e.c.*	Vehicle	2
180601	Travel related to taking class	Vehicle	2
180602	Travel related to extracurricular activities	Vehicle	2
180603	Travel related to research/homework	Vehicle	2
180604	Travel related to registration/administrative activities	Vehicle	2
180682	Travel related to education (except taking class)	Vehicle	2
180699	Travel related to education, n.e.c.*	Vehicle	2
180701	Travel related to grocery shopping	Vehicle	2
180702	Travel related to purchasing gas	Vehicle	2
180703	Travel related to purchasing food (not groceries)	Vehicle	2
180704	Travel related to shopping, ex groceries, food, and gas	Vehicle	2
180782	Travel related to shopping (except grocery shopping)	Vehicle	2
180799	Travel related to consumer purchases	Vehicle	2
180801	Travel related to using childcare services	Vehicle	2
180802	Travel related to using financial services and banking	Vehicle	2
180803	Travel related to using legal services	Vehicle	2

180804	Travel related to using medical services	Vehicle	2
180805	Travel related to using personal care services	Vehicle	2
180806	Travel related to using real estate services	Vehicle	2
180807	Travel related to using veterinary services	Vehicle	2
180899	Travel rel. to using prof. & personal care services, n.e.c.*	Vehicle	2
180901	Travel related to using household services	Vehicle	2
180902	Travel related to using home main./repair/decor./construction svcs	Vehicle	2
180903	Travel related to using pet services (not vet)	Vehicle	2
180904	Travel related to using lawn and garden services	Vehicle	2
180905	Travel related to using vehicle maintenance & repair services	Vehicle	2
180999	Travel related to using household services, n.e.c.*	Vehicle	2
181001	Travel related to using government services	Vehicle	2
181081	Travel related to using government services	Vehicle	2
181002	Travel related to civic obligations & participation	Vehicle	2
181099	Travel rel. to govt svcs & civic obligations, n.e.c.*	Vehicle	2
181101	Travel related to eating and drinking	Vehicle	2
181199	Travel related to eating and drinking, n.e.c.*	Vehicle	2
181201	Travel related to socializing and communicating	Vehicle	2
181202	Travel related to attending or hosting social events	Vehicle	2
181203	Travel related to relaxing and leisure	Vehicle	2
181283	Travel related to relaxing and leisure	Vehicle	2
181204	Travel related to arts and entertainment	Vehicle	2
181205	Travel as a form of entertainment	Vehicle	2
181299	Travel rel. to socializing, relaxing, & leisure, n.e.c.*	Vehicle	2
181301	Travel related to participating in sports/exercise/recreation	Vehicle	2
181302	Travel related to attending sporting/recreational events	Vehicle	2

181399	Travel related to sports, exercise, & recreation, n.e.c.*	Vehicle	2
181401	Travel related to religious/spiritual practices	Vehicle	2
181499	Travel rel. to religious/spiritual activities, n.e.c.*	Vehicle	2
181501	Travel related to volunteering	Vehicle	2
181599	Travel related to volunteer activities, n.e.c.*	Vehicle	2
181601	Travel related to phone calls	Vehicle	2
181699	Travel rel. to phone calls, n.e.c.*	Vehicle	2
181801	Security procedures related to traveling	Vehicle	2
181899	Security procedures related to traveling, n.e.c.*	Vehicle	2
189999	Traveling, n.e.c.*	Vehicle	2

Table C.5: Description of ASHRAE climate zones, included CBSAs within and the representative (mean) F_{INF} .

ASHRAE Climate Zone	Description	CBSAs Included in This Study	Mean Residential F_{INF}
1A	Very hot, humid	Miami, FL	0.5374
1B	Very hot, dry	Phoenix, AZ	0.5374
2A	Hot, humid	Houston, TX; Orlando, FL; San Antonio, TX; Tampa, FL	0.5154
2B	Hot, dry	Riverside, CA	0.4311
3A	Warm, humid	Atlanta, GA; Dallas, TX; Charlotte, NC	0.4855
3B	Warm, dry	San Diego, CA	0.4599
3C	Warm, marine	Los Angeles, CA	0.4898
4A	Mixed, humid	Baltimore, MD; New York, NY; Philadelphia, PA; St. Louis, MO; Washington, DC	0.5143
4B	Mixed, dry	Boston, MA	0.4528
4C	Mixed, marine	Portland, OR; San Francisco, CA; Seattle, WA	0.4977
5A	Cool, humid	Detroit, MI; Chicago, IL	0.4919
5B	Cool, dry	Denver, CO	0.4467
6A	Cold, humid	Minneapolis, MN	0.4665
6B	Cold, dry		0.4567
7A	Very cold		0.4612
7B	Subarctic		0.4501

Table C.6: Average relative activity intensity to daily mean for each microenvironment.

Microenvironment	Relative Activity Intensity to Daily Mean (Pre-Pandemic)	Relative Activity Intensity to Daily Mean (Para-Pandemic)
Residential	0.9226	0.9298
Commercial	1.032	1.059
Vehicle	1.342	1.286
Outdoors	1.853	2.076